DETERMINANTS OF OBSTETRIC FISTULA IN ETHIOPIA: AN APPLICATION OF BINARY AND MULTILEVEL LOGISTIC REGRESSION MODELS

BY

ABEBE DEBU LIGA

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APPROVAL SHEET-1

This is to certify that the thesis entitled **"Determinants of Obstetric Fistula in Ethiopia: an application of Binary and Multilevel Logistic Regression Models"**, submitted in partial fulfillment of the requirements for the degree of Master of Science in Biostatistics with the graduate program of the department of Statistics, University of Gondar and is a record of original research carried out by **Abebe Debu Liga, Id. No. GUR/5101/05** under my supervision and no part of the thesis has been submitted for any other degree or diploma.

The assistance and the help received during the course of this investigation have been duly acknowledged. Therefore, I recommend that the thesis would be accepted as partial fulfillment of the requirement for Master of Science.

______________________	____________	____________
Advisor	**Signature**	**Date**

APPROVAL SHEET-2

We, the undersigned, members of the board of examiners of the final open defense by Abebe Debu have read and evaluated his thesis entitled **"Determinants of Obstetric Fistula in Ethiopia: an application of Binary and Multilevel Logistic Regression Models"** and examined the candidate. This is therefore to certify that the thesis has been accepted in partial fulfillment of the requirements for the degree of Master of Science in statistics with specialization of Biostatistics.

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DECLARATION

I declare that the thesis is my original work, has not been submitted to any other university for achieving any academic degree or diploma awards and all source of materials used for the thesis have been duly acknowledged.

Declared by:

Name: Abebe Debu Liga_

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Date: __________________

“ በእውኑ ለእግዚአብሔር የሚሳነው ነገር አለን? (ዘፍ. 18፡14) ”

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LIST OF ABBREVIATIONS

AGQ	Adaptive Gaussian Quadrature
AIC	Akaikes Information Criterion
AIDS	Acquired Immune Deficiency Syndrome
BIC	Bayesian Information Criterion
CSA	Central Statistical Agency
EDHS	Ethiopian Demographic and Health Survey
FIGO	International Federation of Gynecology and Obstetrics
ICC	Intra Class Correlation Coefficient
IGLS	Iterative Generalized Least Squares
KL	Kullback Leibler
LR	Likelihood Ratio
MCMC	Markov Chain Monte Carlo
ML	Maximum Likelihood
MLE	Maximum Likelihood Estimates
MoH	Ministry of Health
MQL	Marginal Quasi Likelihood
OF	Obstetric Fistula
ORC	Operational Research Center
PQL	Penalized Quasi Likelihood
RIGLS	Reweighted Iterative Generalized Least Squares
RVF	Rectovaginal Fistula
UNFPA	United Nations Population Fund
UNICEF	United Nations International Children's Emergency Fund
VVF	Vesicovaginal Fistula
WHO	World Health Organization

ABSTRACT

Obstetric fistula is a maternal morbidity creating devastating health problems for the women who are affected. Continuous and uncontrollable leaking of urine or faeces from the vagina can lead to life changing stigmatization for women in third world countries. This study examined and identifies the determinants of obstetric fistula in Ethiopia based on the Ethiopian demographic and health survey (EDHS, 2005) data conducted by Central Statistical Agency (CSA). The survey collected information on a total of 14,070 women were interviewed face to face on their background characteristics as well as reproductive health issues, out of which 3178 women were complete measurements and considered in this study. In order to meet our objective descriptive, multiple logistic regression and multilevel logistic regression statistical techniques were used for data analysis using demographic, socio-economic, health and environmental related variables as explanatory variable and status of obstetric fistula as response variable. The results of multiple logistic regression showed that geographical region, place of residence, educational status, age at first birth, age at first marriage, employment status, place of delivery and follow up of antenatal care during pregnancy are a significant determinant factors of obstetric fistula in Ethiopia. The results of multilevel logistic regression analysis showed that the random intercept and fixed coefficient model provided the best fit for the data under consideration. The variance of the random component related to the intercept term was found to be statistically significant implying differences in prevalence of obstetric fistula among the regions. It also found that place of residence, educational status, age at first birth, age at first marriage, employment status, place of delivery and follow up of antenatal care were significant determinant factors of variations of prevalence of obstetric fistula among regions. However, the significant predictors did not show underlying variation from region to region. Integrated women health intervention programs including provisions of antenatal care during pregnancy, access to delivery at health facility, awareness to risk of early marriage and early pregnancy have to be strongly implemented in order to reduce the high incidence of obstetric fistula.

Key words: Obstetric fistula, logistic regression, multilevel logistic analysis, EDHS.

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

Obstetric fistula is a childbirth injury usually caused by unrelieved, prolonged obstructed labor. Obstructed labor can develop during the second stage of labor, when the fetus cannot fit through the birth canal because the pelvis is too small, the baby is too big or if there is a mal presentation. If the woman in labor does not die, the pressure of the baby's head on the mother's pelvis leads to the death of tissue in the birth canal which creates a hole called an obstetric fistula. From this hole, urine or faeces constantly leak. The majority of women also deliver a stillborn baby. Fistula is completely preventable if obstructed labor is diagnosed early and if appropriate timely intervention occurs, which often includes the performance of a caesarean section (Wall, 2012). Women suffering from fistula live with chronic urinary and fecal incontinence, the social effects of which include divorce, abandonment and abuse. Many women report feeling shame about their condition and therefore alienate themselves from friends and family (Barone, 2010).

Obstetric fistula is a maternal morbidity creating devastating health problems for the women who are affected. Continuous and uncontrollable leaking of urine or faeces from the vagina can lead to life changing stigmatization for women in third world countries, a problem that has not been existing in the developed world at the last century (Karen M., 2009). Estimated numbers have shown that approximately two million women worldwide are living with an obstetric fistula and each year there are 50,000-100,000 new cases arising (Pope *et al*., 2011). The high prevalence indicates that vaginal fistula is a substantial health issue and that the health system is failing to meet the need of treatment of reproductive complications (Bangser *et al*., 2011).

Before the medical advances of the 20th century, fistula was quite common in Europe and the United States. Today, obstetric fistula is rare in high-income countries or in countries where emergency obstetric care is widely available. On the other hand, it is a childbearing-related injury that has been neglected in the developing world, despite the devastating impact it has on the lives of women (UNFPA, WHO and FIGO, 2005). In developing countries like Ethiopia, where the per capita income is very low, financial restrictions have considerable significance. Although access to emergency obstetric care plays a pivotal role in the genesis of fistula, malnutrition, early marriage, poverty and illiteracy also add a huge contribution to the development of fistula (Tafesse *et al*., 2006).

WHO has described vaginal fistulas as “the single most dramatic aftermath of neglected childbirth”. Vaginal fistulas are widespread in developing nations, mainly in Sub-Saharan African and South Asian countries, where the social culture encourages marriage at a young age, often shortly after the girls’ first menstrual period between the ages of 9 to 15 (Narcisi, 2010). In many of these cases the first pregnancy is following soon after marriage (Karen, 2009). Prior to mature age, the pelvis of these women is not fully developed, and chronic malnutrition can also further constraint its dimensions.

The incidence rates of obstetric fistula in countries with high maternal mortality rates could be as high as 2 to 3 cases per 100 women (Sunil and Sagna, 2009). Ethiopia has one of the highest maternal mortality rates in the world, and it is estimated that each year more than 500,000 Ethiopian women and girls develop disabilities from complications during pregnancy and child birth (Ministry of Health of Federal Democratic Republic of Ethiopia, 2003). In an unpublished national survey by the Addis Ababa Hamlin Fistula Hospital (Prevalence of Obstetric Fistula in Rural Ethiopia 2005), it is estimated that the incidence of obstetric fistula in rural Ethiopia was found to be 2.2 per 1000 women of reproductive age and also 9,000 of new cases occur every year in Ethiopia, of which only 1,200 are surgically repaired. The immediate consequences of such damage are urinary incontinence, fecal incontinence, and excoriation of the vulva from the constant leakage of urine and feces. Other problems include anemia, foot drop, contractures at the knee or hip joints, and depression. The most common fetal outcome is still birth (Muleta *et al*., 2008).

Women affected by obstetric fistula are often abandoned by their husbands, stigmatized by the community, physically debilitated and even blamed for their condition. Social isolation and abandonment often lead to low self-esteem, depression and prolonged emotional trauma (Wall, 2006).

1.2 Statement of the Problem

Maternal mortality claims 358,000 lives per year worldwide, and nowhere is the problem more profound than in resource-poor countries. The reduction of maternal mortality has been a major international health goal since 1990, and for the first time, global maternal deaths appear to be on the decline from 500,000 deaths in 1990 to 358,000 in 2008 (WHO, UNICEF, UNFPA and the World Bank, 2010). However, much of this decline has been in the global north, while little progress has been made in the poorest countries of the world. In Sub-Saharan Africa, there has been very little improvement (Hill, 2007), despite the fact that these country accounts for the majority of maternal deaths worldwide (WHO, UNICEF, UNFPA and the World Bank, 2010), as well as the highest rates of obstetric fistula (Lewis and De Bernis, 2006).

Obstetric fistula remains a major public health problem in developing world where unattended obstructed labor is common and maternal mortality is unacceptably high. It is a tragedy in developing world because of illiteracy, poverty, ignorance and lack of health facilities (Dangal *et al*., 2013). An obstetric fistula is preventable and treatable condition, the untreated condition remains in developing countries. Ethiopia is one example of developing countries with poor maternal health care as well as high prevalence of obstetric fistula (WHO, 2005). In Ethiopia approximately 26,000 women living with this disability with an additional 9000 new cases annually (Muleta *et al*., 2008). Typical fistula patients in Ethiopia are young peasant girls who are married in their early teens to farmers with little or no education. The girls are given heavy tasks in the household and are poorly educated. They have no access to any health institution during pregnancy and labor, are often helped during labor by women of the village at home, and deliver a dead baby after being in labor for days (Muleta, 2006).

Ethiopian MoH reported 86.7% of the Ethiopian population has access to primary health care services; however, a substantial number of births 94% were delivered at home in 1999-2004. Only 6 percent of births were delivered with the assistance of a trained health professional, i.e., a doctor, nurse, or midwife, and 28 percent were assisted by a traditional birth attendant. The majority of births are attended by a relative or some other person (61%). Five percent of all births are delivered without any type of assistance at all.

Despite the relatively better primary health service coverage available, health service utilization rate is very low (0.32 %). Hence, the country has one of the lowest antenatal cares (52.1%), postnatal care (19%) and institutional delivery care (16.4%) coverage though progressively increasing every year (MoH, 2007).

Many research findings have documented about the most important immediate clinical causes of obstetric fistula. But particularly for Ethiopia, the underlying factors and the different social consequences of the problem before and after treatment are not yet fully identified and adequately documented. Understanding the epidemiology of obstetric fistula and its determinants helps to design appropriate interventions on the basis of scientific evidences. As a result, this study tries to identify the risk factors associated with determinants of obstetric fistula in Ethiopia using binary and multilevel logistic models.

1.3 Objectives of the Study

1.3.1 General Objective

The general objective of this study is to examine the determinant factors associated with the prevalence of obstetric fistula in Ethiopia.

1.3.2 Specific Objectives

- To identify cause of factors that explains the variation among women suffering from obstetric fistula between and within regions.
- Assess the effect of socio-economic, demographic, environmental and health related factors associated with the occurrence of obstetric fistula.
- To determine the prevalence of obstetric fistula in Ethiopia.

1.4 Significance of the Study

Since contribution of woman's health facility is the basic development aspect of a country, there is a need to identify determinant factors which might influence obstetric fistula in Ethiopia. The outcome of this research will provide information to researchers and stakeholders to take intervention actions towards key determinant factors of obstetric fistula. This study is expected to contribute its part by filling the information gap concerning determinant of obstetric fistula in Ethiopia.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 The Pathophysiological Process behind Fistula Forming

The medical term fistula regards to any abnormal passage way connecting two epithelium-lined organs. Obstetric fistulas are the outcome of obstructed, prolonged labor accounting for 76 to 97 percent of the fistulas that sometimes goes on for three to four days. An obstructed labor is described as the immobility of the fetus in the birth canal, which can become stuck and fail to progress after the head has descended into the birth canal. The obstructed labor can result in interrupted blood flow to tissues in the maternal pelvis, on which the fetus' head is exerting pressure and strain during the process of child delivery. Thus, do tissue necrosis occur and an abnormal connection is formed, resulting in either one of the two principle classifications; vesico-vaginal fistula (VVF) or recto-vaginal fistula (RVF) or both (VVF and RVF), through depending on what bodily organs are affected, urine or stool can pass (Narcisi, 2010).

A fistula forms when obstructed labor puts enough pressure on the soft maternal tissues trapped between the fetus and the woman's pelvic bones to compromise their blood supply. As blood flow is cut off, the tissues eventually cross a threshold at which tissue death occurs. This threshold is affected by many different factors, including the amount of force acting on the tissues, the location at which obstruction occurs, the length of time labor has been obstructed, and the inherent resilience of the affected tissues (itself a complex summation of many interconnected biological factors). Because a complicated interplay of factors sets the threshold at which injury occurs, there is no obvious minimum time limit after which an obstetric fistula will be produced. Relatively short labors less than 12 hours in length may result in a fistula if the conditions for "a perfect storm" are present (Wall, 2012a).

Various studies have shown that obstetric fistula usually affects first time mothers who have labored for several days at home, with no access to emergency obstetric care including life-saving procedures like caesarean section. These women end up with obstructed labor, stillbirths and for those who survive this ordeal; an obstetric fistula often develops (Wall, 2006 and Holme *et al.*, 2007).

2.2 Consequence and Epidemiology of Obstetric Fistula

Obstetric fistula was a global problem, however it was eradicated in Europe and North America following improved obstetric care but the condition remains prevalent in Sub-Saharan Africa and Asia. In Africa, most studies on fistula are hospital based and report incidences ranging between 0.6 and 3.5 per 1,000 deliveries. For instance the estimated national prevalence of obstetric fistula in Ethiopia is 1% of ever married women and in Kenya there are 3,000 new fistula cases annually but only 7.5% are reported and treated (Roka *et al*., 2013). Similarly in Tanzania estimates indicate that between 2500 and 3000 new cases of obstetric fistula occur each year (Mselle *et al*., 2012).

Inequity in health-care access is an underlying cause of maternal morbidity in general. Fistula tends to affect the most marginalized members of society: young, poor, illiterate women living in remote areas. Contributing factors for obstetric fistula include poverty, malnutrition, inadequate health systems, detrimental traditional practices, and lack of skilled attendants, limited access to emergency Caesareans, unequal gender relations, and the contributing factors of an often poor economic situation. Fistula can affect all women not only adolescents. For adolescents, pregnancy and childbirth are especially dangerous since they are not physically mature, which increases the risk of obstructed labor. Preventing adolescent pregnancies, by enabling wider access to information and services and stopping child marriages, would decrease the risk of pregnancy-related morbidity within this highly vulnerable group (UNFPA, 2012).

The medical and social consequences of obstetric fistula can be life-shattering for women, their children and families. In almost 90 percent of fistula cases, the baby is stillborn or dies within the first week of life (Wall *et al*., 2004). If a woman survives prolonged or obstructed labor, she may be left with a severe, disabling injury in her birth canal. A woman with fistula is not only left incontinent but may also experience neurological disorders, orthopedic injury, bladder infections, painful sores, kidney failure or infertility. The odor from constant leakage combined with misperceptions about its cause often results in stigma and ostracism by communities. Many women with fistula are abandoned by their husbands and families and are excluded from daily family and community life. They may find it difficult to secure income or support there by depending on their poverty. Their isolation may affect their mental health, resulting in depression, low self-esteem and even suicide (General Assembly, 2012). Obstetric fistula has far reaching effects on physical, social, economic and psychological impact on affected women, their husbands, children and friends. This impact is accentuated by the constant leaking of urine, faeces and blood as a result of a hole that forms between the vagina and the bladder and or rectum (Kimani, 2014).

Despite the high incidence of fistulas in Ethiopia, many women do not seek medical help promptly; findings suggest that delay in the decision to seek care may be caused by different factors such as lack of understanding of complications, the low status of women, socio-cultural barriers and physical barriers such as mountains, rivers and lack of transport added to the delay in reaching care (Kijugu, 2009).

2.3 Review of Variable that determine Obstetric fistula

Information from various literature shows that obstetric fistula appears to be linked to certain social-economic and cultural factors including young age at marriage, poverty and illiteracy, living in rural areas with lack of emergence obstetric care (Wall, 2006; Holme *et al* and Johnson 2007; Nathan *et al*., 2008). Obstetric fistula has serious social and economic consequences on the lives of these women. Majority of the women are abandoned by their spouses who cannot stand the smell of urine. Major risk factors for obstetrics fistula include early age at pregnancy, short stature, illiteracy, poverty, not attending antenatal care and rural place of residence or living far away from a health facility (Roka *et al*., 2013).

A cross sectional community study in Sudan conducted by (Mohamed *et al*., 2008) showed that a total of 52 patients with vesico-vaginal fistula presented to the Fistula center in Khartoum teaching hospital more than two third of patients (80.8%) being of low-socioeconomic status. This may explain why girls are married early. 44.2% of patients were 18-24 years old, 58.8% were teenagers when married <18 years old. While 75% of the patients were illiterates, 62.8% were married to illiterate husbands. They also showed that labor was responsible for 90.4% of VVF of whom 59.6% were primiparous, 42.6% delivered at home. They also found that 55.3% of cases stayed in labor for more than 24 hours, as long as 53.2% were not in regular antenatal care. As a result, they revealed that the victim of obstetric fistula was mostly a young woman, a primigravida, who was poor, illiterate, not attend on regular antenatal care and being in labor more than 24 hours. Most deliveries were carried at home, attended by traditional birth attendants in most cases.

A study conducted in West Pokot by (Mabeya, 2003) found that prolonged labor was a major causative factor of obstetric fistula. The majority of fistulas in West Pokot were seen to occur in women aged 20 years and below. The majority of fistula incidents occurred in women delivering their first child. These were also women who had no formal education or had attained primary education at the lowest level and had no specific occupation.

According to (Zheng and Anderson, 2009) found that in eighteen retrospective and hospital-based studies in Ethiopia and Nigeria reported women often acquired fistula at a young age and with the first pregnancy. Furthermore, patient's reported that high divorce rates and low educational levels. Patients in Ethiopia traveled 700 km or more and walked an average of 12.3 hours to reach the hospital. Another study by (Muleta, 2004) found that distance, financial constraints, and poor knowledge were the most frequently cited problems for delays in decision and transport to health institutions during labor. However, in general, the women had little or no access to healthcare, prenatal or emergency obstetric care.

A study done by (Kayondo *et al.,* 2011) in Kenya found that Women with large fistulae were six times more likely to have unsuccessful repair than those with small fistulae ($P < 0.01$) using multivariate analysis. Most of the fistula patients were primiparous (41.6%), had some formal education (61%) and (45.5%) were still married despite having a fistula. 70% of the participants had antenatal care attendance in the causative pregnancy and (76.6%) delivered from a health facility. Most of the participants had been delivered by caesarean section (59.7%) and the prenatal mortality was as high as 90%. Majority of the participants had been in labor for an average of 2.5 days and the mean age at fistula development was 24 years.

A study using a Cox proportional hazard regression model conducted in India by (Singh *et al*., 2014) found that the hazard ratio of having stillbirths were significantly higher among women with any obstetric complications compared to women with no obstetric complications. The adverse pregnancy outcome in a previous pregnancy was the largest risk factor for likelihood of developing similar type of adverse pregnancy outcome in the current pregnancy**.**

(Tebekaw, 2011) using a logistic regression model to evaluate socio-cultural and demographic determinants of obstetric fistula in Ethiopia found that 32% of rural women experienced obstetric fistula, and surprisingly 70% of them were not treated for obstetric fistula. Women with secondary and higher education were less likely to be affected by obstetric fistula (OR=0.28) compared to those with no education. Women with five or more total children ever born were 3.8 times more likely to be affected by OF compared to those with zero total children ever born.

A study conducted in three districts and one hospital in Tanzania in 2003 and in four districts in Uganda in 2005 by (Bangser *et al*., 2011) found that a total of 137 patients (61 in Tanzania and 76 in Uganda) the median age of Women in Tanzania when they sustained obstetric fistula was 23 years and 19 years in Uganda. Nearly 44% of women in both countries had parity two or higher when they sustained fistula, while approximately 53% of women in both countries were primipara. They also found that Forty-five percent of the women in Tanzania and 51% of the women in Uganda had planned to deliver at a health care facility, while the remaining had planned to deliver at home.

Similarly, a study carried out by (Tom *et al*., 2008) to evaluate prospective results after first-time surgery for obstetric fistulas in East African women found that a total of 639 patients with 647 fistulas underwent first-time repair. The study comprised the 581 (90.9%) patients whose fistulas had been caused by obstructed labour. Their mean age was 27 years, 70% were shorter than 156 cm, and 30.8% had completed primary education. In 45.1%, the fistula patient was primigravida; prenatal survival was 11.5%. Mean duration between onset of the fistula and surgical treatment was 36.4 months. 40.6% of the fistula patients lived separated from their partner. Overall closure rate of the fistulas was 93.8%. The same study by Kimani, 2014 found that less than one third of the women who were married when they sustained fistula were separated and divorced as a result of the fistula.

Muleta (2004) used a logistic regression model and a cross tabulation to evaluate Socio-Demographic Problem and Obstetric Experience of Fistula Patients found that the mean age of fistula patients who admitted to the hospital was 22 years, age at first marriage was 14.7 and mean age at the causative delivery was 17.8. The result revealed that early marriages are more likely to expose to obstetric fistula. Early age at pregnancy has been identified as one of the factors leading to increasing risks of fistula with particular reference to adolescent's women (12-19 years). This is prominent where early marriages are common for socio-cultural and religious reasons (Ampofo, 1990).

A study conducted by (Michele *et al*., 2013) on the long term outcomes of vaginal mesh versus native tissue repair for anterior vaginal wall prolapsed, from this a five year surgery for recurrent prolapsed was similar between vaginal mesh and native tissue groups (10.4% vs 9.3%), P = 0.70 and the result of adjusted Cox model were similar (HR: 0.93, 95% CI: 0.83, 1.05). It shows that the use of mesh for anterior prolapsed was associated with an increased risk of repeat surgery.

A meta- analysis conducted by (Ahmed and Holtz, 2007) showed that an average of 85% of the women suffering from obstetric fistula experience fetal loss, and to make matters worse, while they feel mentally tormented and devastated, they typically find themselves violently thrashed into an intense environment where they are not given the chance to mourn.

Tesfaye (2013) used the Cox proportional hazard analysis to evaluate time to recovery of obstetric fistula at Yirgalem Fistula Hospital in Ethiopia found that older ages at first marriage, weight less than 50kg, height greater than 150cm, follow up of antenatal care, delivery at health center, duration of labor for less than 2 day, vaginal delivery, length and width of fistula less than 5cm and intact of urethra significantly contribute to shorter stay in hospital to treated and physically cured.

On the other hand education plays an important role in the occurrence of obstetric fistula, in maternal mortality and morbidity in general (Tebeu, 2009). When girls are allowed to attend school, marriage and childbearing are delayed, thereby providing girls more time for skeletal and physiological development (Wall L.L., 2012b). Education and literacy provide women with information about maternal health processes (Harrison, 1997) and raise their general standard of living (Wall L.L., 2012b). Conversely, several studies have demonstrated a correlation between low levels of education and obstetric fistula prevalence. In Malawi, (Yeakey, 2009) found that 60% of women with obstetric fistulas had fewer years or no education. Similarly, (Nisar *et al.*, 2010) working in Pakistan, found that 81.5% of women with fistulas were illiterate and that 63% of their husbands were illiterate.

CHAPTER THREE

3. METHODOLOGY

3.1 Data Source

The data source for this study was the Ethiopian Demographic and Health Survey (EDHS) conducted by central Statistical Agency (CSA) in 2005. It is the second survey conducted in Ethiopia as part of the worldwide Demographic and Health Survey Project. The survey was primarily designed to collect data on fertility, family planning, maternal care, infant and child mortality, childhood illnesses, malaria, nutrition, prevalence of female genital cutting, prevalence of obstetric fistula, knowledge of AIDS and other sexually transmitted infections in Ethiopia. The 2005 Ethiopia Demographic and Health Survey was designed to provide estimates for the health and demographic variables of interest for the following domains: Ethiopia as a whole; urban and rural areas (each as a separate domain); and 11 geographic regions (9 regions and 2 city administrations).

The 2005 EDHS is nationally representative surveys of individual women were interviewed face to face on their background characteristics as well as reproductive health issues. The survey was selected in two stages. In the first stage, 540 clusters (145 urban and 395 rural) were selected from a list of enumeration areas from the 1994 Population Census. In the second stage, a complete listing of households was carried out in each selected cluster. The 2005 EDHS collected a complete household listing was prepared for each selected cluster and households. Households were systematically selected from each cluster for participation in the survey. In the survey, women were asked whether they have ever experienced obstetric fistula (OF) in their life. Only 3,178 of them responded about their experience on OF which would be considered in this study.

3.2 Variables in the study

3.2.1 Dependent Variable

The response variable for the i^{th} individual is represented by Y_i and it measures women's experience of obstetric fistula and it is dichotomized with 1 being experienced and 0 being not experienced.

3.2.1 Independent Variables

Predictor variables are those variables which are presumed to affect or determine a dependent variable. Since based on the reviewed literatures, some of the common predictors that are expected to influence on determinants of obstetric fistula in Ethiopia were recorded as given below for the purpose of the analysis. In this study possible determinants of obstetric fistula were grouped as demographic, socio-economic, Environmental and health related factors.

Demographic related factors

In this study the independent variables such as age at first marriage, age at first birth and marital status are expected to demographic risk factors.

Socio-Economic related factors

In this study educational status, employment status and wealth index are included in socio-economic factors.

Environmental and health related factors

Environmental and health related factors which will be included in this study are region, place of residence, place of delivery, body mass index and frequency of antenatal visits.

Table 3.1: Covariates Description with their Coding for obstetric fistula.

Variables	Categories	Coding
Age at first Marriage	Below 15 years	0(ref)
	15 – 19 years	1
	20 – 24 years	2
	25 years and above	3
Region	Addis Ababa	0(ref)
	Tigray	1
	Affar	2
	Amahara	3
	Oromia	4
	Somali	5
	Ben-Gumuz	6
	SNNP	7
	Gambela	8
	Harari	9
	Dire Dawa	10

Age at first Birth	Below 15 years 15 – 19 years 20 – 24 years 25 years and above	0(ref) 1 2 3
Educational Status	No education Primary Secondary and Higher	0(ref) 1 2
Marital Status	Married Widowed Divorced	0(ref) 1 2
Employment Status	Currently working No currently working	0(ref) 1
Body Mass Index(as proxy for women nutritional status)	Normal Underweight Over Weight Obesity	0(ref) 1 2 3
Wealth Index	Poor Middle Rich	0(ref) 1 2
Place of Residence	Urban Rural	0(ref) 1
Place of Delivery	Home Health Center Others	0(ref) 1 2
Frequency of Antenatal Visits	No antenatal visit 1-3 days 4-6 days 7 days and Above Do not Know	0(ref) 1 2 3 4

3.3 Methodology

3.3.1 Binary Logistic Regression Model

Regression methods are essential to any data analysis which attempts to describe the relationship between a response variable and any number of predictor variables. Logistic regression analysis extends the techniques of multiple regression analysis in which the outcome variable is categorical. Logistic regression allows one to predict a discrete outcome, such as group membership, from a set of predictor variables that may be continuous, discrete, dichotomous, or a mix of any of these (Gellman and Hill, 2007). In this paper, the risk factors for obstetric fistula were identified by using logistic regression analysis.

In clinical situations, the status of a patient is assessed by the presence or absence of a disease. There are many factors to consider which may or may not correlate with the incidence of the disease. There has been numerous retrospective medical research studies published each year that review past medical records and charts of former patients to help determine some of the risk factors (or causing agents) of diseases that are of interest. Finding the risk factors and the potential risk factors can help prevent the development of the disease. All of the diseases and nearly all of the risk factors considered are categorical variables (variables taking on two or more possible values). Hosmer and Lemeshow (1989), two prominent statisticians, state that “the logistic regression model has become the standard method of analysis in this situation.”

Logistic regression is a statistical technique for predicting the probability of an event, given a set of predictor variables. The procedure is more sophisticated than the linear regression procedure. The binary logistic regression procedure empowers one to select the predictive model for dichotomous dependent variables. It describes the relationship between a dichotomous response variable and a set of explanatory variables. The explanatory variables may be continuous or discrete. The logistic model, as a non-linear regression model, is a special case of generalized linear model (McCullagh and Nelder, 1989) where the assumptions of normality and constant variance of residuals are not satisfied.

Generally, when the dependent variable is dichotomous (such as presence or absence, success or failure and etc.) binary logistic regression is used. The logistic regression is also preferred to multiple regression and discriminant analysis as it results in a meaningful interpretation, it is mathematically flexible and easily used distribution and it requires fewer assumptions (Hosmer and Lemeshow, 1989).

The relationship between the predictor and response variables is not a linear function in logistic regression; instead the logistic regression function which is the logit transformation of the success probability is used. Consider a collection of k predictor variables denoted by the vector $X' = (X_1, X_2, \dots, X_k)$. Then the conditional probability that i^{th} women has experienced by obstetric fistula given the vector of predictor variables X_i is denoted by $P(y = 1 / X) = \pi(X)$. Then, the logistic regression model for explaining data is given by;

$$\pi(X) = \frac{\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k)}{1 + \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k)} \quad (3.1)$$

Then, the logit or log-odds of having y=1 is modeled as a linear function of the explanatory variables as:

$$\operatorname{logit}(\pi(X)) = \log\left(\frac{\pi(X)}{1 - \pi(X)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \,; 0 \le \pi(X) \le 1 \quad (3.2)$$

Where, β_0 is a constant of the equation and $\beta_1, \ldots \beta_k$ are the coefficients of the predictor variables. The estimated logistic coefficient β_j's are interpreted as the change in the log-odds for every unit increase or decrease (depending on the variable change in X_i) holding other predictors constant (Agresti, 1996).

3.3.1.1 Assumptions of Logistic Regression

1. Logistic regression predicts the odds of an event occurring, which is based on the probability of that event occurring. Precisely, the odds of an event occurring is given by:

$$\text{Odds} = \frac{\text{Probablity of an event occur}}{\text{Probablity of an event not occur}} = \frac{\pi}{1 - \pi}$$

2. The response variable must be categorical.
3. Logistic regression does not assume a linear relationship between the dependent and the independent variables, but the logit regression equation should have a linear relationship with the logit form of the dependent variable.
4. The dependent variable need not be normally distributed, but typically assume its distribution is within the range of the exponential family of distributions (such as normal, Poisson, binomial, gamma); binary logistic regression assume binomial distribution of the response.
5. The dependent variable need not be homoscedastic for each level of the independents; meaning that there is no homogeneity of variance assumption: variances need not be the same within categories.
6. Normally distributed error terms are not assumed.
7. Logistic regression needs larger samples than linear regression because maximum likelihood coefficients are large sample estimates.

3.3.1.2 Parameter Estimation in Logistic Regression Model

The most commonly used method of estimating the parameters of a logistic regression model is the method of Maximum Likelihood (ML). In logistic regression, the likelihood equations are non-linear explicit functions of the unknown parameters. Therefore, we use a very effective and well known as the Newton-Raphson iterative method also known as iteratively reweighted least squares algorithm to solve the equations (Hosmer and Lemeshow, 2000). Hence, in this study the maximum likelihood estimation technique is used to estimate parameters for the model.

Suppose the logistic model $\pi(X_i) = P(y_i = 1 / X_i) = \frac{e^{X_i\beta}}{1+e^{X_i\beta}}$. Since observed values of $Y(Y_i,\ i = 1,2,\ldots,n)$ are independently distributed as Bernoulli random variables, the likelihood function of Y is the joint density function given by:

$$L(\beta / Y) = \prod_{i=1}^{n} P(y_i = 1 / X_{i1},\ldots,X_{ik}) = \prod_{i=1}^{n} \left[\frac{e^{X_i\beta}}{1+e^{X_i\beta}}\right]^{y_i} \left[\frac{1}{1+e^{X_i\beta}}\right]^{1-y_i} \tag{3.3}$$

The maximum likelihood estimates of the parameters β are obtained by maximizing the log-likelihood function which is given by:

$$\text{Log } L(\beta / Y) = \sum_{i=1}^{n} \left\{ y_i \log\left[\frac{e^{X_i\beta}}{1+e^{X_i\beta}}\right] + (1-y_i)\log\left[\frac{1}{1+e^{X_i\beta}}\right]\right\} \tag{3.4}$$

The maximum likelihood estimates of the parameters are found by the derivation of the log-likelihood function with respect to each β's and set each equation to zero which is given as:

$$\frac{d\text{Log } L(\beta / Y)}{d\beta_j} = 0, \quad j = 1,2,\ldots,k$$

3.3.1.3 Model Building and Variable Selection

The number of variables to be included in the model should be the minimum possible that is parsimonious and deliver optimum information. In this study the variable selection process begins with a univariate analysis of each variable. Tests to determine whether a systematic relation or association between each predictor variable with the response variable exists are made before the final model was selected. A univariate logistic regression and a likelihood ratio (LR) chi-square test would be employed to examine the importance of each predictor variables to the outcome variable (Hosmer and Lemeshow, 2000).

In order to determine the number of predictor variables to be considered in a study, some literature suggest that at least 50 cases for each predictor while others recommend 10 cases per predictor. In general, there should be significantly fewer independent variables than the ordinary least squares regression. In this regard, a rule of thumb is that there should be no more than one independent for each 10 cases in the sample. In applying this rule of thumb, if there are categorical independent predictors such as dichotomous, the number of cases should be considered to be the lesser of the groups.

Another approach to variable selection is to use stepwise selection procedure. Stepwise selection of variables has been widely used in linear regression. In this method, variables are selected for either inclusion or exclusion from the logistic regression model in a sequential fashion based on statistical criterion that checks for the importance of variables. The importance of variables is defined in terms of a measure of the statistical significance of the coefficient for the variable. In stepwise selection procedure, backward selection and/or forward selection procedure are used (Hosmer and Lemeshow 2000).

In Forward selection procedure, we add terms sequentially until further additions do not improve the fit. The backward selection on the other hand begins with a complex model and sequentially removes terms. Stepwise selection procedure is the combination of forward selection and backward selection to identify the best model (Hosmer and Lemeshow 2000).

The final decision on the inclusion of each predictor variable will be made on the examination of the Wald statistic for the variable, and comparing each estimated coefficient of the particular variable on the multiple logistic regression models with the univariate estimate of the model containing only that predictor. Variables that do not contribute to the model based on these criteria would be eliminated and a new model should be fit. The new model would be compared with the old model through the LR test. Also, the estimated coefficients for the remaining variables were compared to those from the full model. In view of this (deletion, refitting or verifying) was performed. Having obtained a model that contains the essential variables, the need to include interaction terms in the model would be assessed by creating the appropriate product of the variables in question. Assessment of the significance of each interaction term would be made using a LR test. Interactions that do not contribute to the improvement of the model would be discarded and the model with main-effects should be maintained.

3.3.1.4 Goodness of Fit of the Model

After fitting the logistic regression model or once a model has been developed through the various steps in estimating the coefficients, there are several techniques involved in assessing the appropriateness, adequacy and usefulness of the model. First, the importance of each of the explanatory variables would be assessed by carrying out statistical tests of the significance of the coefficients. Then the overall goodness of fit of the model would be tested (Agresti, 1996).

The goodness of fit measures how well the model describes the response variable. Assessing goodness of fit involves investigating how close values are predicted by the model with that of observed values (Bewick and Jonathan, 2005). The comparison of observed to predicted values using the likelihood function is based on the statistic called deviance.

$$D = -2\sum_{i=2}^{n}\left[(y_i)\ln\left(\frac{\hat{p}_i}{y_i}\right) + (1 - y_i)\ln\left(\frac{1 - \hat{p}_i}{1 - y_i}\right)\right] \tag{3.5}$$

For purposes of assessing the significance of an independent variable, the value of D is compared with and without the independent variable in the equation as given below:

$$D = D_o - D_L$$

Where D_o is the deviance of model without the explanatory variable and D_L is the deviance of model with the explanatory variable included.

The goodness of fit (D) process evaluates predictors that are eliminated from the full model, or predictors (and their interactions) that are added to a smaller model. In general, as predictors are added or deleted, log-likelihood decreases or increases. The question in comparing models is whether the log-likelihood decreases or increases significantly with the addition or deletion of predictor(s) in the model. D has a chi-square distribution with degree of freedom equal to the difference between the numbers of parameters estimated in the two models.

Additionally, the ability of the model to discriminate between the two groups defined by the response variable is evaluated. Finally, if possible, the model is validated by checking the goodness of fit and discrimination on a different set of data from that which will be used to develop the model (Bewick and Jonathan, 2005). The Pearson's Chi-square, the likelihood ratio tests, Hosmer and Lemeshow Goodness of fit Test and the Wald tests are the most commonly used to measures of goodness of fit for categorical data (Hosmer and Lemeshow, 1989).

Likelihood-Ratio Test

An alternative and widely used approach to test the significance of a number of explanatory variables is to use the likelihood ratio test. This is appropriate for a variety of types of statistical models. Agresti (1990) argues that the likelihood ratio test is better, particularly if the sample size is small or the parameters are large. The G^2 test statistic is defined as two times the natural log of the ratio of likelihood functions of two models evaluated at their Maximum Likelihood Estimates (MLEs). The likelihood-ratio test uses the ratio of the maximized value of the likelihood function for the full model (L_1) over the maximized value of the likelihood function for the reduced model (L_0). For each of the variables removed from the full model one at time, MLEs are computed and likelihood function L_0 is calculated. Therefore, the likelihood-ratio test statistic is given by:

$$G^2 = -2\ln\left[\frac{L_0}{L_1}\right] = -2\{\ln L_0 - \ln L_1\} \tag{3.6}$$

Where L_0 is the likelihood function of the reduced model and L_1 is the likelihood function of the full model evaluated at the MLEs.

This natural log transformation of the likelihood functions yields an asymptotically chi-squared statistic. G^2 is distributed with degrees of freedom equal to the difference between the numbers of parameters estimated in the two models (Menard, 2002). It is important to test the null hypothesis that all population logistic regressions coefficients are not significance difference except the constant one.

The Hosmer and Lemeshow Test

The final measure of model fit is the Hosmer and Lemeshow goodness of fit statistic, which measures the correspondence between the actual and predicted values of the dependent variable. Hosmer and Lemeshow chi-square test is used to test the overall model goodness of fit test when we have many predictor variables or some of the predictor variables are continuous.

Hosmer and Lemeshow test is based on grouping cases in deciles in the sense that it is obtained by applying a chi-square test on a 2×g contingency table. The contingency table is constructed by cross classifying the dichotomous dependent variable with approximately g=10 groups in which the groups are formed by partitioning the predicted probabilities using the percentiles of the predicted event probability. It evaluates the goodness of fit by creating these 10 ordered groups of subjects and then compares in each observed group to the number predicted by the logistic regression model. The 10 ordered groups are created based on their estimated probability in such a way that those with estimated probability below 0.1 form one group, and so on, up to those with probability 0.9 to 1. Each of these categories is further divided into two groups based on the actual observed outcome variable (success and failure).

The expected frequencies for each of the cells are obtained from the model. If the model is good, most of subject with success are classified in the higher deciles of risk and those with failure in the lower deciles of risk and if the significance of the test is less than 0.05, then the model does not adequately fit the data. Thus, the test statistic is a chi-square statistic with a desirable outcome of non-significance, indicating that the model prediction does not significantly differ from the observed. The Hosmer and Lemeshow test statistic is given by:

$$\hat{C} = \sum_{k=1}^{g} \frac{(O_k - E_k)^2}{V_k} \tag{3.7}$$

Where $E_k = nP_k$, $V_k = nP_k(1 - P_k)$, g is the number of groups, O_k is observed number of events in the k^{th} group, E_k is expected number of events in the k^{th} group, V_k is a variance correction factor for the k^{th} group and P_k is predicted risk for the k^{th} group.

If the observed number of events differs from what is expected by the model, the statistic $\hat{C}$ will be large and there will be evidence against the null hypothesis that the model is adequate to fit the data. This statistic has an approximate chi-square distribution with $(g - 2)$ degree of freedom (Hosmer and Lemeshow, 1989).

The Wald Test

The Wald statistic is an alternative test, which is commonly used to test the significance of individual logistic regression coefficients for each independent variable (that is to test the null hypothesis in logistic regression model that a particular logit coefficient is zero).

In logistic regression we have a binary outcome variable and one or more explanatory variables. For each explanatory variable in the model there will be an associated parameter. The Wald test, described by Polit (1996) and Agresti (1990), is used to test whether the parameter associated with an explanatory variable is zero or not. For a particular explanatory variable, or group of explanatory variables, if the Wald test is significant, then we would conclude that the parameters associated with these variables are not zero, so that the variables should be included in the model. It is used to test the significance of individual coefficients in the model and is given by:

$$W = Z^2 = \left[\frac{\hat{\beta}_j}{s.e.\hat{\beta}_j}\right]^2 \sim \chi^2(1) \quad , \qquad j = 1,2, \dots p \tag{3.8}$$

Under the null hypothesis $H_0: \hat{\beta}_j = 0$ ($j = 1,2, \dots p$) the statistics W is approximately distributed as chi-square with one degree of freedom (Agresti, 2008).

3.3.1.5 The Logistic Regression Diagnostics

The next important step in logistic regression model building is to perform diagnostics analysis to study the influence of observations. It is important to examine the adequacy of the resulting model in logistic regression. There are comparable diagnostics that should be used to identify data problems. The logistic regression provides a variety of such statistics (Agresti, 2008).

Leverage Value:-it is used for detecting observation that have a large impact on the predicted values. Unlike linear regression, the leverage values in logistic regression depend on the dependent variable scores and the design matrix. It's obtained from the diagonal element of the hat matrix, H, which is given as

$$H = V^{\frac{1}{2}} X (X' V X)^{-1} X' V^{\frac{1}{2}} \tag{3.9}$$

Where h_j is the j^{th} diagonal element of the $J \times J$ hat matrix, H is the leverage of observation i. Here, V is the $J \times J$ diagonal matrix with elements $m_j \hat{\pi}_j \left(1 - \hat{\pi}_j\right)$ and X is the $J \times (p + 1)$ design matrix. The greater the value of $h_j (i.e. h_j > 1)$, the more potential that observation has for influencing the model fit.

Cook's Distance:-Cook (1977) suggests diagnostic measures of the extent of changes in the estimated model coefficients as a result of removing a case from the data. Cases for which Cook's distance is large have substantial influence on both the estimate of β and on fitted values and deletion of these cases may result in significant changes. If Cook's distance of a case is greater than 1, then it is potential outlier. Cook's D_i statistics is obtained as:

$$D_i = \frac{\left(\hat{\beta}_i - \hat{\beta}_{(i)}\right)' X'V X\left(\hat{\beta}_i - \hat{\beta}_{(i)}\right)}{ps^2} \tag{3.10}$$

Alternatively, D_i is also obtained as:

$$D_i = \frac{{r_i}^2}{p}\left(\frac{h_i}{1 - h_i}\right) \tag{3.11}$$

Where r_i is the standardized residual, h_i is the i^{th} diagonal element of H and it is computed from the full regression and p is the number of unknown parameters.

DfBetas:-For each parameter estimate, a DfBetas diagnostic is calculated for each observation. This is the standardized difference in the parameter estimate due to deleting the observation, and it can be used to assess the effect of an individual observation on each estimated parameter of the fitted model. These measures are useful for detecting observations that are causing instability in the selected coefficients. If DfBetas of a case is greater than 1, then it is potential outlier. The influential observations for the individual regression coefficients are identified by $\mathrm{DfBetas}_{\,j(i)}$, $j = 0, 1, 2, \dots, p$ and obtained as:

$$\mathrm{DfBetas}_{\,j(i)} = \frac{\hat{\beta}_j - \hat{\beta}_{j(i)}}{s_i\sqrt{c_{jj}}} \tag{3.12}$$

Where c_{jj} is the $(j + 1)^{th}$ diagonal element from$(X'VX)^{-1}$, $\mathrm{DfBetas}_{\,j(i)}$ is measures the change in $\hat{\beta}_j$ in multiples of its standard error.

3.3.2 Review of Multilevel Modeling

Multilevel analysis is a methodology for the analysis of data manifesting complex variability, with a focus on nested source of variability. The best approach to the analysis of multilevel data is an approach that represents within-group as well as between group relation within a single level analysis, where 'group' refers to the units at the higher levels of the nesting hierarchy. Probability models are used to represent the within-group and between-group variability. In other word, we conceive of variation within groups and variation between groups as random variability.

In this study we considered two-level hierarchical analysis where women are nested within regions. The modeling for such hierarchical data can be expressed by statistical models called random coefficient models. Multilevel analysis is an approach to analyzing such hierarchical data. The main statistical model of multilevel analysis is the hierarchical generalized linear model, for example multilevel logistic regression is an extension of the generalized linear model that includes random coefficients.

The 2005 EDHS data set is used for this study is based on multistage stratified cluster sampling. The appropriate approach to analyzing obstetric fistula data from this survey is therefore based on nested sources of variability. Here the units at lower level are women who are nested within units at higher level (regions). Due to this nested structure, the odds of women's experiencing obstetric fistula are not independent, because women from the same cluster (region) may share common exposure to the outcome of interest. The response variable for this study is "women's experience of obstetric fistula" which is binary and hence multilevel logistic regression model is a natural choice for modeling. The multilevel logistic regression analysis considers the variations due to hierarchy structure in the data. It allows the simultaneous examination of the effects of group level and individual level variation-dependence of observations within and between groups.

To keep the discussion on multilevel logistic regression models simple and taking in to account the data to be analyzed in this study we concentrate on the case of two-levels. Since multilevel model allow not only independent variable at any level of hierarchical structure but also at least one random effect above one level group (Snijders and Bosker, 1999).

3.3.2.1 Multilevel Logistic Regression Model

We first consider a two-level model for binary outcomes with a single explanatory variable. The extension to three or higher levels is straight forward. Let Y_{ij} is the binary outcome variable, coded '1' or '0', being experienced or not experienced of obstetric fistula, associated with level-one unit i nested within level two units j. Assume P_{ij} be the probability that the response variable equals 1, $P_{ij} = Pr(Y_{ij} = 1/X_{ij})$ represent the probability of experiencing obstetric fistula for i^{th} women in the region j and also $1 - P_{ij}$ is the probability of i^{th} women not experiencing obstetric fistula in the j^{th} region. Like the ordinary logistic regression, P_{ij} is modeled using the link function, logit. The two-level logistic regression model can be given as:

$$\mathrm{logit}(p_{ij}) = \log\left[\frac{p_{ij}}{1-p_{ij}}\right] = \beta_0 + \beta_1 x_{ij} + U_{0j} \tag{3.13}$$

Where, U_{0j} is the random effect at level 2; without U_{0j} equation (3.13) can be considered as standard logistic regression model. Therefore, conditional on U_{0j}, the Y_{ij} 's can be assumed to be independently distributed as Bernoulli random variables. Here U_{0j} is a random quantity and follows a normal distribution with mean zero and variance $\sigma^2{}_u$(Snijders and Bosker, 1999).

By rearranging equation (3.13), we can split into two models: one for level 1 and the other for level 2.

$$\mathrm{logit}(p_{ij}) = \log\left[\frac{p_{ij}}{1-p_{ij}}\right] = \beta_{0j} + \beta_1 x_{ij} \qquad \text{[Model: level 1]}$$

$$\beta_{0j} = \beta_0 + U_{0j} \qquad \text{[Model: level 2]}$$

The intercept consists of two terms: a fixed component (β_0) and a group-specific component, random effect, U_{0j}.

3.3.2.2 Heterogeneous Proportions

In this study the data structure of two-level logistic regression is a collection of N groups (units at level-two (regions)) and within region j (j=1, 2 …N) random sample of n_j level one units. The outcome variable is dichotomous and denoted by $Y_{ij}(i = 1,2, \ldots, n_j;\ j = 1,2, \ldots, N)$ for level-one unit i nested within level two units j. The outcome is coded as 1 and 0; 1 for "women's being experienced by obstetric fistula", 0 for otherwise. The total sample size is $M = \sum_{j=1}^{N} n_j$. If one does not taking any explanatory variable in to account, the probability of success is constant in each j group and it is denoted by P_{ij}. In a random coefficient model, the groups are considered as being taken from a population groups and the success probability in the groups, P_{ij} are regarded us random variables defined in the population. The dichotomous outcome can be represented as the sum of the probability and a residual.

$$Y_{ij} = P_{ij} + \varepsilon_{ij}$$

i.e. the outcome for individual i in group j, which is either 0 or 1, is expressed as the sum of probability (average proportion of success) in this group plus some individual dependent residual. This residual (like all other residual) has mean zero but for this dichotomous variable it has the peculiar property that it can assume only the value P_j and $1 - P_j$. A further peculiar property is fact that given the value of the probability P_j, the variance of the residual is

$$\mathrm{Var}(\varepsilon_{ij}) = P_{ij}(1 - P_{ij})$$

Since the outcome variable is coded 0 and 1, the group sample average is the proportion of successes in group j given by:

$$\hat{P}_j = \frac{1}{n_j}\sum_{i=1}^{n_j} Y_{ij} \tag{3.15}$$

$\hat{p}_j$ is an estimate for the group-dependent probability. Similarly, the overall sample average is the overall proportion of successes ($\hat{p}$) and is given by:

$$\hat{P} = \frac{1}{M}\sum_{j=1}^{N}\sum_{i=1}^{n_j} Y_{ij} \tag{3.16}$$

This is an estimate for the overall probability of success (P).

Testing Heterogeneity of Proportions

For the proper application of multilevel analysis the first logical step is to test heterogeneity of proportions between groups. Here we present two commonly used test statistics that are used to check for heterogeneity. To test whether there are indeed systematic differences between the groups, the well-known chi-square test for contingency table can be used. In this case the chi-square test statistic is:

$$\chi^2 = \sum_{j=1}^{N} n_j \left[\frac{\hat{p}_j - \hat{p}^2}{\hat{p}(1 - \hat{p})}\right] \tag{3.17}$$

This statistic follows approximately a chi-square distribution with $N-1$ degrees of freedom. This chi-squared distribution is an approximation valid if the expected number of success $(n_j\hat{p}_j)$ and of failures $(n_j(1-\hat{p}_j))$ in each group all are at least one while 80 percent of them are at least 5 (Agresti, 1996). This condition will not always be satisfied, and the chi-square test then may seriously lead to wrong conclusions.

A second test of heterogeneity of proportions was proposed by Commenges and Jacqmin (1994). The test statistic is:

$$Z = \frac{\sum_{j=1}^{N}\left\{n_j^{2}(\hat{p}_j-\hat{p})^2\right\} - M(\hat{p}(1-\hat{p}))}{\hat{p}(1-\hat{p})\sqrt{2\sum_{j=1}^{N} n_j(n_j-1)}} \tag{3.18}$$

The statistic Z follows the standard normal distribution for large value of M. Thus, large calculated values of this statistic are indication of heterogeneous proportions. In the statistic Z the numerator contains a weight of n_j^2 whereas chi-square test uses a weight n_j. This shows that the two tests combine the groups in different ways. Hence, when the group sizes n_j are different, it is possible that the two tests may lead to different outcomes. The test statistic Z is shown to have high power over the chi-square test and can be applied whenever there are many groups, even with small group sizes, provided that no single group dominates (Snijders and Bosker, 1999).

Estimations of Between and Within Group Variance

The true variance between the group dependent probabilities, i.e. the population values of $\mathrm{Var}(P_j)$, is given by:

$$\hat{\tau}^2 = S^2_{\text{between}} - \frac{S^2_{\text{within}}}{\tilde{n}} \tag{3.19}$$

Where $\tilde{n}$ is defined as: $\tilde{n} = \frac{1}{N-1}\left[M - \frac{\sum_{j=1}^{N} n_j^2}{M}\right]$

For dichotomous outcome variables, the observed between group variance is closely related to the chi-square test statistic given in equation 3.17.

$$S^2_{between} = \frac{\hat{p}(1-\hat{p})}{\tilde{n}\,(N-1)}\chi^2$$

Where χ^2 is given in equations (3.17).

The within group variance in case of a dichotomous outcome variable is a function of group averages which is given by:

$$S^2_{within} = \frac{1}{M-N}\sum_{j=1}^{N} n_j\, p_j(1-p_j)$$

Multilevel logistic regression can be employed in the simplest case without explanatory variables (usually called empty model) and also with explanatory variables by allowing only the intercept term or both the intercept and the slopes (regression coefficients) to vary randomly. It mainly assumed that the varying coefficients have multivariate normal distribution (Snijders and Bosker, 1999).

3.3.2.3 The Empty Multilevel Logistic Regression Model

The empty two-level model for a dichotomous outcome variable refers to a population of groups (level-two units) and specifies the probability distribution for group-dependent probabilities p_j in $Y_{ij} = p_j + \varepsilon_{ij}$ without taking further explanatory variables into account. We focus on the model that specifies the transformed probabilities $f\left(p_j\right)$ to have a normal distribution. This is expressed for a general link function f (p), by the formula;

$$f\left(p_j\right) = \beta_o + U_{oj} \tag{3.20}$$

Where, β_o is the population average of the transformed probabilities and U_{oj} is the random deviation from this average for group j. If f(p) is the logit function, then $f\left(p_j\right)$ is just the log-odds for group j. Thus, for the logit link function, the log-odds have a normal distribution in the population of groups, which is expressed by:

$$\text{logit}\left(p_j\right) = \beta_o + U_{oj} \tag{3.21}$$

For the deviations U_{oj}, it is assumed that they are independent random variables with a normal distribution with mean zero and variance σ_0^2. This model does not include a separate parameter for the level-one variance (Snijders and Bosker, 1999). This is because the level-one residual variance of the dichotomous outcome variable follows directly from the success probability which is given by: $\mathrm{Var}(\varepsilon_i) = P_j(1 - P_j)$. The probability corresponding to the average value β_0, denoted by π_0 and defined by, $f(\pi_0) = \beta_0$.

For the logit function, then so-called logistic transformation of β_0, is defined by:

$$\pi_0 = \mathrm{logistic}(\beta_0) = \frac{\exp(\beta_0)}{1 + \exp(\beta_0)} \tag{3.22}$$

Note that due to the non-linear nature of the logit link function, there is no a simple relation between the variance of probabilities and the variance of the deviations U_{0j} (Snijders and Bosker, 1999). An approximate variance of the probability given by:

$$\mathrm{var}(P_j) \approx (\pi_0(1 - \pi_0))^2 \sigma_0^2 \tag{3.23}$$

Note that an estimate of population variance $\mathrm{var}(P_j)$ can be obtained by replacing sample estimates of π_0 and σ_0^2 . The resulting approximation can be compared with the non-parametric estimate, $\hat{\tau}^2$ which was given in equation (3.19).

3.3.2.4 The Random Intercept Multilevel Logistic Regression Model

In the random intercept model, the intercept is the only random effect meaning that the groups differ with respect to the average value of the response variable, but the relation between explanatory and response variables cannot differ between groups. We assume that there are variables which potentially explain the observed success and failure. These variables are denoted by $X_h, (h = 1,2, \dots, k)$ with their values indicated by X_{hij}. Since some or all of those variables could be level one variable, the success probability is not necessarily the same for all individual in a given group (Snijders and Bosker, 1999). Therefore, the success probability depends on the individual as well as the group, and is denoted by P_{ij}. The outcome variable is split into an expected value and residual as:

$$Y_{ij} = P_{ij} + \varepsilon_{ij}$$

The random intercept model expresses the log-odds, i.e. the logit of P_{ij}, as a sum of a linear function of the explanatory variables. That is,

$$\operatorname{logit}(P_{ij}) = \log\left(\frac{p_{ij}}{1 - p_{ij}}\right) = \beta_{oj} + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \cdots + \beta_k x_{kij} = \beta_{oj} + \sum_{h=1}^{k} \beta_h x_{hij} \qquad (3.24)$$

Where the intercept term β_{oj} is assumed to vary randomly and is given by the sum of an average intercept β_o and group-dependent deviations U_{oj}, that is

$$\beta_{oj} = \beta_o + U_{oj}$$

As a result we have:

$$\operatorname{logit}(P_{ij}) = \beta_o + \sum_{h=1}^{k} \beta_h X_{hij} + U_{oj} \qquad (3.25)$$

Solving for P_{ij} we have:

$$P_{ij} = \frac{e^{\beta_o + \sum_{h=1}^{k} \beta_h x_{hij} + U_{oj}}}{1 + e^{\beta_o + \sum_{h=1}^{k} \beta_h x_{hij} + U_{oj}}} \qquad (3.26)$$

Thus, a unit difference between the X_h values of two individuals in the same group is associated with a difference of β_h in their log-odds, or equivalently, a ratio of $\exp(\beta_h)$ in their odds.

Equation (3.24) does not include a level-one residual because it is an equation for the probability P_{ij} rather than for the outcome Y_{ij}. Note that in the above equation $\beta_o + \sum_{h=1}^{k} \beta_h x_{hij}$ is the fixed part of the model. The remaining U_{oj} is called the random part of the model. It is assumed that the residual U_{oj} are mutually independent and normally distributed with mean zero and variance σ_o^2.

3.3.2.5 The Random Coefficient Multilevel Logistic Regression Model

In logistic regression analysis, linear models are constructed for the log-odds. The multilevel analogue, random coefficient logistic regression is based on linear models for the log-odds that include random effects for the groups or other higher level units.

Consider explanatory variables which are potential explanations for the observed outcomes. Denote these variables by $X_1, X_2, \ldots, X_k$. The values of $X_h (h = 1, 2, \ldots, k)$ are indicated in the usual way by X_{hij}. Since some or all of these variables could be level-one variables, the success probability is not necessarily the same for all individuals in a given group. Therefore, the success probability depends on the individual as well as the group, and is denoted by P_{ij}.

Now consider a model with group-specific regressions of logit of the success probability, $\text{logit}(P_{ij})$, on a single level one explanatory variable X,

$$\text{logit}(P_{ij}) = \log\left(\frac{p_{ij}}{1 - p_{ij}}\right) = \beta_{oj} + \beta_{1j} x_{1ij} \quad (3.27)$$

The intercepts β_{oj} as well as the regression coefficients or slopes, β_{1j} are group dependent. These group dependent coefficients can be split into an average coefficient and the group dependent deviation:

$$\beta_{oj} = \beta_o + U_{oj}$$

$$\beta_{1j} = \beta_1 + U_{1j}$$

Substitution into (3.27) leads to the model

$$\text{logit}(P_{ij}) = \log\left(\frac{p_{ij}}{1 - p_{ij}}\right) = (\beta_o + U_{oj}) + (\beta_1 + U_{1j}) x_{1ij} = \beta_o + \beta_1 x_{1ij} + U_{oj} + U_{1j} x_{1ij} \quad (3.28)$$

There are two random group effects, the random intercept U_{oj} and the random slope U_{1j}. It is assumed that the level two residuals U_{oj} and U_{1j} has both zero mean given the value of the explanatory variable X. Thus, β_1 is the average regression coefficient and β_o is the average intercept. The first part of equation (3.28) , $\beta_o + \beta_1 x_{1ij}$ is called the fixed part of the model whereas the second part $U_{oj} + U_{1j} x_{1ij}$ is called the random part of the model.

The term $U_{oj} + U_{1j} x_{1ij}$ can be regarded as a random interaction between group and predictors (X). This model implies that the groups are characterized by two random effects: their intercept and their slope. These two groups' effects (U_{oj}, U_{1j}) are independent and identically distributed. The random intercept, random slope variances and covariance between the random effects are called variance components and given by the following equations respectively:

$$\mathrm{Var}(U_{oj}) = \sigma_{00} = {\sigma_0}^2$$

$$\mathrm{Var}(U_{1j}) = \sigma_{11} = {\sigma_1}^2$$

$$\mathrm{Cov}(U_{oj}, U_{1j}) = \sigma_{01}$$

The model for a single explanatory variable discussed above can be extended by including more variables that have random effects. Suppose that level one explanatory variable $X_1, X_2, \ldots X_k$ and consider the model where all predictor variables have varying slopes and random intercept is given by:

$$\mathrm{logit}(P_{ij}) = \log\left(\frac{p_{ij}}{1 - p_{ij}}\right) = \beta_{oj} + \beta_{1j}x_{1ij} + \beta_{2j}x_{2ij} + \cdots + \beta_{kj}x_{kij} \tag{3.29}$$

Letting , $\beta_{oj} = \beta_o + U_{oj}$ and $\beta_{hj} = \beta_h + U_{hj}$ where, $h = 1, 2, \ldots, k$, we have:

$$\mathrm{logit}(P_{ij}) = \log\left(\frac{p_{ij}}{1 - p_{ij}}\right) = \beta_o + \sum_{h=1}^{k} \beta_h x_{ij} + U_{oj} + \sum_{h=1}^{k} U_{hj}x_{ij} \tag{3.30}$$

The first part $\beta_o + \sum_{h=1}^{k} \beta_h x_{ij}$ is called the fixed part of the model, and the second part, $U_{oj} + \sum_{h=1}^{k} U_{hj}x_{ij}$ is called the random part of the model. The random variables or effects $U_{0j}, U_{1j}, \ldots,$ U_{kj} are assumed to be independent between groups but may be correlated within groups. So the components of the vector $(U_{0j}, U_{1j}, \ldots, U_{kj})$ are independently distributed as a multivariate normal distribution with zero mean vector and variances and co-variances matrix Ω given by:

$$\Omega = \begin{pmatrix} \sigma_0^2 & . & \ldots & . \\ \sigma_{01} & \sigma_1^2 & \ldots & . \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{0k} & \sigma_{1k} & \cdots & \sigma_k^2 \end{pmatrix}$$

3.3.2.6 Intra-class Correlation Coefficient (ICC)

The other fundamental reason for applying multilevel analysis is the existence of intra-class (intra-regional) correlation arising from similarity of occurence of obstetric fistula in the same region compared to those of different regions. The intra-class correlation coefficient (ICC) measures the proportion of variance in the outcome explained by the grouping structure. ICC can be calculated using an intercept-only model. This model can be derived from Equation (3.29) by excluding all explanatory variables, which results in the following equation: ($\text{logit}(p_j) = \beta_{o+} U_{oj}$).

The ICC is then calculated based on the following formula:

$$\text{ICC} = \frac{\delta_{uo}^2}{\delta_{uo}^2 + \delta_e^2} \tag{3.31}$$

Where, δ_e^2 variance of individual (lower) level units

In multilevel logit model level one residual variance $\delta_e^2 = \frac{\pi^2}{3} \approx 3.29$ (Snijders and Bosker, 1999) this formula can be reformulated as:

$$\text{ICC} = \frac{\delta_{uo}^2}{\delta_{uo}^2 + 3.29} \tag{3.32}$$

3.3.2.7 Estimation and Testing Technique for Multilevel logistic model

Parameter estimation for multilevel logistic model is not straightforward like the methods for ordinary logistic regression. The most common methods for estimating multilevel logistic models are based on likelihood. Among the methods, Marginal Quasi Likelihood or MQL [Goldstein (1991), Goldstein and Rasbash (1996)] and Penalized Quasi Likelihood or PQL [Laird (1978); Breslow and Clayton (1993)] are the two prevailing approximation procedures. Both MQL and PQL are based on Taylor series expansion to achieve the approximation. Based on the first and second term of Taylor expansion, MQL and PQL are often known as first order MQL and second-order MQL, first-order PQL and second-order PQL respectively. After applying these quasi likelihood methods, the model is then estimated using iterative generalized least squares (IGLS) or reweighted IGLS (RIGLS) [Goldstein (2003)].

Besides, there are other estimation methods: Maximum Likelihood Method (several simulation based; McCulloch (1997)), Bayesian methods using Markov Chain Monte Carlo (MCMC), Adaptive Gaussian Quadrature (AGQ) and the Iterative Bootstrap method. Using MCMC simulation technique has come to the front of statistical research over the last one and half decade [Gelfand *et al*. (1990)] and also it is being used with greater extent in multilevel modeling recently. An important part of modeling involves testing parameters and models to see which parts of the multilevel model are statistically important. For fixed coefficients of multilevel logistic regression tests about parameters are done using the Wald test. The random part of multilevel logistic regression parameters is estimated based on t-test or Z-test. Parameter estimation in hierarchical generalized linear models is more complicated than the hierarchical linear models. The most frequently used kind of approximation method used is based on a first-order or second-order Taylor series expansion of the link function.

3.3.2.8 Model Comparison

3.3.2.8.1 Akaikes Information Criterion (AIC)

It is the expected estimated relative Kullback-Leibler (KL) distance, where the K-L distance is the minimum distance between a model and full reality (Taper, 2004). And it is given by:

$$\mathrm{AIC} = -2 \times \ln(\mathrm{likelihood}) + 2 \times \mathrm{k} \qquad (3.33)$$

3.3.2.8.2 Bayesian Information Criterion (BIC)

It is also known as the Schwarz criterion after Gideon Schwarz and virtually identical to the minimum description length criterion (Taper, 2004). The formula is given as:

$$\mathrm{BIC} = -2 \times \ln(\mathrm{likelihood}) + \ln(\mathrm{N}) \times \mathrm{k} \qquad (3.34)$$

Where, in the above both equations k is number of estimated parameters, N is the number of observations used in estimation or more precisely the number of independent terms in the likelihood. AIC and BIC can be viewed as measures that combine fit and complexity. Fit is measured negatively by $-2 \times \ln$ (likelihood); the larger the value, the worse the fit. Complexity is measured positively, either by $2 \times \mathrm{k}$ (AIC) or $\ln(\mathrm{N}) \times \mathrm{k}$(BIC). Given two models fit on the same data, the model with the smaller value of the information criterion is considered to be better (Akaike, 1974 and Schwarz, 1978).

CHAPTER FOUR

4. RESULTS AND DISCUSSIONS

4.1 Statistical data analysis

The purpose of this chapter is to analyze different factors that determine obstetric fistula in Ethiopia using data from 2005 Ethiopian Demographic and Health Survey (EDHS). The analysis is carried out in three parts. In the first part, results of descriptive statistics are presented; in the second part, we identified and examined determinants of obstetric fistula using multiple logistic regression analysis with the help of SPSS software. Finally, multilevel logistic regression model was employed to examine the factors and variations of obstetric fistula across regions using the help of STATA software package.

4.2 Results of Descriptive Statistics

A total of 3178 women were included in the study from EDHS 2005 sample. The initial population consisted of 14,070 women were interviewed face to face on their background characteristics as well as reproductive health issues. Out of which, 3178 women have complete measurements and were considered in this study and others were excluded due to incompleteness of data on the variables which are considered in the analysis. From the sampled data, the prevalence of obstetric fistula was about 18.8% in Ethiopia. Additionally, the prevalence is also shown graphically in Figure 3.1 (See Appendix 3).

The major socio-economic and demographic background characteristics of the respondents are presented in Table 4.1 below. Among 3178 respondents 84.6% are resides in rural area and 15.4% are resides in urban area. The higher prevalence of obstetric fistula was occurred for a woman resides in rural area (21.2%) as compared to women's resides in urban area (5.4%).

Table 4.1 also shows, among the total respondents 31.9% of them had no work and higher prevalence of obstetric fistula were observed (24.7%). Majority of women (51.2%) were first marriage at in the age range between 15-19 years, while 32.1% of women's were first marriage at in the age range below 15 years, about 13.8 % of women were first marriage at in the age range 20-24 years and the remaining 2.9% of women were first marriage at in the age range 25 years and above. The highest prevalence of obstetric fistula was observed for women whose first marriage at in the age range 25 and above (25.7%) followed by women's whose first marriage at in the age range below 15 years (21.5%).

According to Table 4.1, age at first birth was found to be an important determinant factor of obstetric fistula. The proportion of women suffered from obstetric fistula is highest among teenage women's, age at first birth below 15 years (29.9%). The proportion of women suffered from obstetric fistula is also considerably higher for women first birth at in the age range between 15-19 years (19.4%) compared to those whose first birth at in the age range 20-24 years (15.5 %) and women's first birth at in the age range 25 years and above (13.8 %).

Furthermore, Table 4.1 shows that, the proportions of women suffered from obstetric fistula are varied by educational status. Majority of respondents 75.2% of them had no education. While, only 16.5% and 8.3% of them had primary education level and secondary and higher education level respectively. The highest prevalence was observed for women who had no education (19.4%).

Among the socio-economic and demographic determinant factors age at first marriage, age at first birth, educational status, wealth index and employment status were found to have a significant effect on the incidence of obstetric fistula at 5% levels of significance.

Table 4.1: Distribution of Socio-economic and Demographic related determinant factors of obstetric fistula in Ethiopia

Variables	Categories	Counts (%)	Being Experienced OF		d.f	Chi-Square	P-Value
			No	Yes			
Age at first Marriage	Below 15 years	1022(32.1)	78.5%	21.5%	3	18.542	0.000*
	15 – 19 years	1626(51.2)	84.4%	16.6%			
	20 – 24 years	439(13.8)	81.1%	18.9%			
	25 years and above	91(2.9)	74.3%	25.7%			
Age at first Birth	Below 15 years	254(8.0)	70.1%	29.9%	3	10.767	0.013*
	15 – 19 years	1820(57.3)	80.6%	19.4%			
	20 – 24 years	886(27.9)	84.5%	15.5%			
	25 years and above	218(6.8)	86.2%	13.8%			
Educational Status	No education	2391(75.2)	80.6%	19.4%	2	253.41	0.000*
	Primary	524(16.5)	83.8%	16.2%			
	Secondary and Higher	263(8.3)	82.1%	17.9%			

Place of Residence	Urban	491(15.4)	94.6%	5.4%	1	176.77	0.000*
	Rural	2687(84.6)	78.8%	21.2%			
Marital Status	Married	2998(94.3)	81.1%	18.9%	2	2.493	0.288
	Widowed	74(2.3)	79.7%	20.3%			
	Divorced	106(3.4)	86.8%	13.2%			
Wealth Index	Poor	1412(44.4)	86.8%	13.2%	2	74.301	0.000*
	Middle	562(17.7)	83.6%	16.4%			
	Rich	1204(37.9)	73.7%	26.3%			
Employment Status	Currently working	2165(68.1)	84.0%	16.0%	1	33.092	0.000*
	No currently working	1013(31.9)	75.3%	24.7%			

*significant at 5%

The major environmental and health related background characteristics of the respondents are presented in Table 4.2. The proportion of women who suffered from obstetric fistula varies from one region to another. The highest prevalence of obstetric fistula was recorded in Amahara (30.8%) followed by Oromia (27.4%) and Gambella (24.1%) as opposed to lowest prevalence which was recorded in Addis Ababa (6.3%) and followed by Benshangul Gumuz (6.4%).

Table 4.2 also shows that there is a significant association between incidence of obstetric fistula and place of delivery ($p<0.001$). Surprisingly, among the whole respondents about 87.1% of them are delivered at their home and the highest prevalence was recorded (20.5%) compared to women were delivered at health center (7.4%) followed by women were delivered at other place (4.5%). This shows that delivering at health center would help to decrease the number of patients that exposed to obstetric fistula.

Moreover, result presented in Table 4.2 showed that antenatal care visit and body mass index are important variables. The highest proportion of women suffered from obstetric fistula was observed among obesity women that means BMI >30 (44.4%) followed by overweight (BMI between 25 and 29.9 (37.1%)) as opposed to the lowest proportion which was recorded in women who have a normal weight (BMI between 18.5 and 24.9) and followed by underweight (BMI<18.5). Similarly, the highest proportions of obstetric fistula were observed among women who do not know about antenatal visit (35.7%) and no antenatal visit (24.2%) as compared to women’s who had taken antenatal care for one and more day during pregnancy.

Table 4.2: Distribution of Environmental and Health related determinant factors of obstetric fistula in Ethiopia

Variables	Categories	Counts (%)	Being Experienced OF		D.f	Chi-Square	P-Value
			No	Yes			
Region	Addis Ababa	144(4.5)	93.7%	6.3%	10	295.804	0.000*
	Tigray	325(10.2)	90.1%	8.9%			
	Affar	194(6.1)	86.7%	13.3%			
	Amahara	465(14.6)	69.2%	30.8%			
	Oromia	574(18.1)	72.6%	27.4%			
	Somali	197(6.2)	85.4%	14.6%			
	Ben-Gumuz	239(7.5)	93.6%	6.4%			
	SNNP	564(17.8)	80.0%	20%			
	Gambela	181(5.7)	75.9%	24.1%			
	Harari	169(5.3)	92.8%	7.2%			
	Dire Dawa	126(4.0)	84.9%	15.1%			
Place of Delivery	Home	2767(87.1)	79.5%	20.5%	2	156.231	0.000*
	Health Center	367(11.5)	92.6%	7.4%			
	Others	44(1.4)	95.5%	4.5%			
Follow up of Antenatal Care	No antenatal visit	2165(68.1)	75.8%	24.2%	4	206.245	0.000*
	1-3 days	453(14.3)	94.4%	5.6%			
	4-6 days	386(12.2)	91.4%	8.6%			
	7 days and Above	160(5.0)	94.6%	5.4%			
	Do not Know	14(0.4)	64.3%	35.7%			
Body Mass Index	Normal	2262(71.2)	82.4%	17.6%	3	35.826	0.000*
	Underweight	764(24)	81.9%	18.1%			
	Over Weight	116(3.7)	62.9%	37.1%			
	Obesity	36(1.1)	55.6%	44.4%			

*significant at 5%

4.3 Binary logistic regression analysis

Multiple logistic regressions were fitted based on chi-square test result of bivariate analysis. Based on results presented in Table 4.1 and 4.2, those predictor variables that are associated with obstetric fistula at 5% level of significance were selected for multiple logistic regression analysis. Multiple logistic regression models were fitted using these predictor variables using forward selection (Likelihood ratio) method. The result presented in Table 4.6 showed that eight of the predictor variables were significantly associated with the incidence of obstetric fistula.

4.3.1 Assessment of Goodness of Fit of the Model

For categorical data, after a logistic regression model has been fitted, a global test of goodness of fit of the resulting model should be performed. It is necessary to see the appropriateness, adequacy and usefulness of the fitted model. The most commonly used techniques are Likelihood-Ratio test, Hosmer and Lemeshow test, R-Square and the Wald goodness of fit test.

Likelihood-Ratio Test

The most common assessment of overall model fit in logistic regression is the likelihood ratio test, which is the chi-square difference between the null model with the constant only and the model containing a set of predictors. Under model summary in Table 4.3, we see that -2Log Likelihood statistics is 2552.525. This statistics show us how much improvement is needed before predictors provide the best possible prediction of the response variable, the smaller the statistics the better the model. The statistics for only intercept model is $-2\text{LLo} = 515.105 + 2552.525 = 3067.63$. The inclusion of the parameters reduced the -2 Log Likelihood statistics by $3067.63 - 2552.525 = 515.105$, which is reflected chi-square for omnibus test. The result ($\chi^2 = 515.105$, $\text{d.f} = 33$, p-value<0.001), shows that the model is adequate, meaning that at least one of the predictors is significantly related to the dependent variable. That is, the null hypothesis is that there is no difference between the model with only a constant and the model with independent variables was rejected (See Appendix 1; Table 1.2).

Table 4.3: Model Summary of Binary Logistic Regression Model

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
2552.525[a]	0.15	0.242

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

The Hosmer and Lemeshow goodness of fit test divides subjects into deciles based on predicted probabilities, then computes a chi-square from observed and expected frequencies in a $10x2$ table (See Appendix 1; Table 1.3). A non-significant chi-square indicates that there is no difference between the observed and the model predicted values and hence estimates of the model adequately fit the data. Since Table 4.4 shows as the p-value is 0.844 and it is greater than 0.05 then, we don't reject the null hypothesis that there is no difference between observed and model predicted values, implying that the model fitted the data well.

Table 4.4: Hosmer and Lemeshow Test

Chi-square	Df	Sig.
4.139	8	0.844

Two additional descriptive measures of goodness of fit presented in the above Table 4.3 are R^2 indices defined by Cox and Snell (1989) and Nagelkerke (1991). These indices are variations of the R^2 concept defined for the ordinary least square regression model. The Nagelkerke R^2 was 24.2% indicating that the explanatory variables were useful in predicting the presence or absence of obstetric fistula in Ethiopia.

Classification Table

A classification table shows the validity of predicted probabilities. The accuracy of the classification is measured by its sensitivity (the ability to predict an event correctly) and specificity (the ability to predict the non-occurrence of an event correctly). The classification Table 4.5 shows that 22.8% of women being experienced obstetric fistula was correctly classified where as 97.1% of the women who being not experienced obstetric fistula was correctly classified. The overall correct prediction was 83.2% which is an improvement over the chance level.

Table 4.5: Classification Table of Model with Predictor Variables

Observed		Predicted		
		Being Experienced Obstetric Fistula		Percentage Correct
		No	Yes	
Being Experienced Obstetric Fistula	No	2508	74	97.1
	Yes	460	136	22.8
Overall Percentage				83.2

Logistic regression diagnostics result

After model fitting, the next important step in logistic regression is model building to perform an analysis of residuals and diagnostics to study the influence of observations and taking appropriate remedial measure. A failure to detect outliers and hence influential cases can have severe distortion on the validity of the inferences drawn from the model. It would be reasonable to use diagnostics to check if the model is adequate or not. The main focus here will be to detect outliers and influential cases that have a substantial impact on the fitted logistic regression model through appropriate graphical methods.

The diagnostic test results for detection of outliers and influential cases are displayed in (Appendix 1; Table 1.5) shows that the maximum values of analog of Cook's influence statistics and DFBETA for each predictor variables, which were less than 1. Hence there is no potential influential observation. Therefore, from the above goodness of fit tests and diagnostic checking, we conclude that the models are adequate.

4.3.2 Results of Multiple Logistic Regression Analysis

Multiple logistic regressions were used to analyze the effect of each independent variable on women's status of obstetric fistula, while controlling for the other independent variables. Accordingly region, place of residence, educational status, age at first birth, age at first marriage, employment status, place of delivery and follow up of antenatal care were found to be significant predictors for prevalence of obstetric fistula at 5% level of significance (see Table 4.6). Thus, the estimated model is given by:

$$\mathrm{logit}\big(\pi(\mathrm{X})\big) = \beta_0 + \sum_{i=1}^{10} \beta_{1i}\mathrm{Reg}_i + \beta_2\mathrm{PlR}_1 + \sum_{j=1}^{2} \beta_{3j}\mathrm{EduSta}_j + \sum_{k=1}^{3} \beta_{4k}\mathrm{Ag1Ma}_k + \sum_{l=1}^{3} \beta_{5l}\mathrm{Ag1Bi}_l + \beta_6\mathrm{EmSt}_1 + \sum_{m=1}^{2} \beta_{7m}\mathrm{PlDel}_{\mathrm{m}} + \sum_{\mathrm{n}=1}^{4} \beta_{8\mathrm{n}}\mathrm{FolAnt}_n$$

Where: $\pi(\mathrm{X}) =$ Predicted probability of obstetric fistula, $\beta_0 =$ constant, $\mathrm{PlR}_1 =$ Place of residence of women's at level 1, $\mathrm{Reg}_i =$ Women's region of level i, $\mathrm{EduSta}_j =$ Educational background of women's at level j, $\mathrm{Ag1Ma}_k =$ Age at first marriage of women's at level k,

$\mathrm{Ag1Bi}_l$ = Age at first birth of Women's at level l, EmSt_1 = Employment status of women's at level 1, $\mathrm{PlDel_m}$ = Place of delivery of level m, FolAnt_n = Follow up of antenatal care of level n.

Therefore, based on the result of Table 4.6, the final logistic regression equation consisting of the significant variables is given by:

$$
\begin{aligned}
\mathrm{logit}\big(\pi(\mathrm{X})\big) = {} & 2.742 + 0.254\mathrm{Reg}_1 + 0.95\mathrm{Reg}_2 + 1.536\mathrm{Reg}_3 + \cdots + 0.669\mathrm{Reg}_{10} + 1.642\mathrm{PlR}_1 \\
& - 2.232\mathrm{EduSta}_1 - 1.609\mathrm{EduSta}_2 - 2.068\mathrm{Ag1Ma}_1 - 1.696\mathrm{Ag1Ma}_2 - 0.416\mathrm{Ag1Ma}_3 \\
& - 0.733\mathrm{Ag1Bi}_1 - 1.719\mathrm{Ag1Bi}_2 - 2.031\mathrm{Ag1Bi}_3 + 0.284\mathrm{EmSt}_1 - 1.570\mathrm{FolAnt}_1 \\
& + \cdots - 0.945\mathrm{FolAnt}_4 - 1.625\mathrm{PlDel}_1 - 0.878\mathrm{PlDel}_2
\end{aligned}
$$

The logistic model showed that the likelihood of having obstetric fistula was significantly associated with geographical regions. Women who living in Amhara region were 4.646 times more likely to have experience of obstetric fistula than Addis Ababa region controlling for other variables in the model (OR=4.646; 95% CI: 2.467-8.750). Similarly Women's who lived in Oromia region were 4.405 times more likely to have experience of obstetric fistula than Addis Ababa controlling for other variables in the model (OR=4.405; 95% CI: 2.270-8.547). Moreover, women's who live in Affar, Somali, SNNP, Gambella and Dire Dawa were more likely to have experience of obstetric fistula than Addis Ababa region. Unlikely the odds of having obstetric fistula among women's live in Tigray, Benshangul gumuz and Harari were not significantly differ from that of women's live in Addis Ababa region.

Table 4.6 also show that place of residence have a significance association with the incidence of obstetric fistula. A woman who reside in rural area were 5.167 times more likely to have obstetric fistula than that of woman's who reside in urban area controlling for other variables in the model (OR=5.167; 95% CI: 3.562-7.495).

The logistic model showed that women educational status is negatively associated with the incidence of obstetric fistula. A woman having primary education was 89.3% less likely to have obstetric fistula than women's who had no education (OR=0.107; 95% CI: 0.068-0.17). Similarly, Women's having secondary and higher education were 80% less likely to suffer obstetric fistula than women who had no education controlling for other variables in the model (OR=0.200; 95% CI: 0.123-0.324).

According to result Table 4.6, we observe that the log of the odds of women being suffered in obstetric fistula was negatively related to age at first marriage. Women whose first marriage at in the age range between 15-19 years were 87.4% less likely to suffer obstetric fistula than women whose first marriage at in the age range <15 years. On the same way, women whose first marriage at in the age range between 20-24 years were 81.7% less likely to suffer obstetric fistula than women whose first marriage at in the age range <15 years controlling for other variables in the model. Similarly, the logistic model showed that age at first birth has also a negative significant association with the incidence of obstetric fistula ($p<0.001$).

The logistic model showed that women's employment status is a significant predictor of the incidence of obstetric fistula. Women who are not currently working were 1.328 times more likely to have experience of obstetric fistula than women's who had currently working controlling for other variables in the model (OR=1.328; 95% CI: 1.063-1.660). The analysis also showed frequency of antenatal care visits has a statistically significant association with the incidence of obstetric fistula ($p<0.001$). The odds of women being experienced obstetric fistula who had taken antenatal care visits for 7 days and above during pregnancy was 87.1% less likely to suffered in obstetric fistula compared to women's who had no antenatal care visit (OR=0.129; CI: 0.053-0.310). Similarly, the odds of women's being experienced obstetric fistula who had taken antenatal care visits for 1-3 days during pregnancy was 79.2% less likely to suffered in obstetric fistula compared to women's who had no antenatal care visit controlling for other variables in the model (OR=0.208; 95% CI: 0.132,0.328).

Furthermore, place of delivery is also a significant factor associated with the incidence of obstetric fistula. Women who delivered from health center were 80.3% less likely to suffer in obstetric fistula compared to women who delivered from their homes controlling for other variables in the model (OR=0.197; CI: 0.104-0.373).

Table 4.6: Maximum likelihood estimates of predicting the incidence of Obstetric fistula in Ethiopia

	Categories	B(S.E.)	Wald	df	Sig.	Exp(B)	95.0% C.I. for EXP(B)	
							Lower	Upper
Region			134.518	10	.000*			
	Addis Ababa(Ref)							
	Tigray	0.254(0.301)	0.712	1	.398	1.289	0.715	2.326
	Affar	0.950(0.331)	8.237	1	.004*	2.585	1.351	4.947
	Amahara	1.536(0.323)	22.614	1	.000*	4.646	2.467	8.750
	Oromia	1.483(0.338)	19.227	1	.000*	4.405	2.270	8.547
	Somali	1.074(0.314)	11.681	1	.001*	2.928	1.581	5.423
	Ben-Gumuz	0.122(0.305)	0.160	1	.689	1.130	0.621	2.054
	SNNP	1.278(0.308)	17.217	1	.000*	3.589	1.963	6.565
	Gambella	1.370(0.313)	19.087	1	.000*	3.934	2.128	7.272
	Harari	0.240(0.317)	0.573	1	.449	1.271	0.683	2.366
	Dire Dawa	0.669(0.321)	4.337	1	.037*	1.952	1.040	3.664
Place of Residence	Urban (Ref)							
	Rural	1.642(0.190)	74.908	1	.000*	5.167	3.562	7.495
Educational Status			96.086	2	.000*			
	No education(Ref)							
	Primary	-2.232(0.235)	89.994	1	.000*	0.107	0.068	0.170
	Secondary & Higher	-1.609(0.246)	42.686	1	.000*	0.200	0.123	0.324
Age at first Marriage			58.369	3	.000*			
	<15 years(Ref)							
	15-19 years	-2.068(0.390)	28.161	1	.000*	0.126	0.059	0.271
	20-24 years	-1.696(0.376)	20.356	1	.000*	0.183	0.088	0.383
	25 and above years	-0.416(0.376)	1.226	1	.268	0.660	0.316	1.378

Age at first Birth	<15 years(Ref)		96.663	3	.000*			
	15-19 years	-0.733(0.243)	9.082	1	.003*	0.481	0.298	0.774
	20-24 years	-1.719(0.195)	78.13	1	.000*	0.179	0.122	0.262
	25 and above years	-2.031(0.336)	36.619	1	.000*	0.131	0.068	0.253
Employment Status	Currently working (Ref)							
	Not currently working	0.284(0.114)	6.218	1	.013*	1.328	1.063	1.660
Follow up of Antenatal Care	No antenatal visit(Ref)		82.661	4	.000*			
	1-3 days	-1.570(0.233)	45.464	1	.000*	0.208	0.132	0.328
	4-6 days	-1.526(0.245)	38.656	1	.000*	0.217	0.134	0.352
	7 days and Above	-2.050(0.448)	20.959	1	.000*	0.129	0.053	0.310
	Do not Know	-0.945(0.894)	1.118	1	.290	0.389	0.067	2.241
Place of Delivery	Home(Ref)		26.733	2	.000*			
	Health Center	-1.625(0.325)	24.96	1	.000*	0.197	0.104	0.373
	Others	-0.878(0.564)	2.423	1	.120	0.416	0.138	1.256
	Constant	2.742(0.526)	27.209	1	.000*	15.512		

*Significant at 5%, Ref = reference category, OR=Odd ratio estimate

4.4 Results of a Multilevel Logistic Regression Analysis

A chi-square test statistic was applied to assess heterogeneity in the proportion of women's who had experience of obstetric fistula among the 11 regions. The test yield χ^2 = 295.804, d.f=10, P<0.001. Thus, there is an evidence for heterogeneity with respect to the incidence of obstetric fistula among regions.

4.4.1 Multilevel Logistic Regression Model Comparison

Table 4.7 shows that the predicted probability of obstetric fistula by Regions with predictors; place of residence, educational status, age at first birth, employment status, age at first marriage, place of delivery and follow up of antenatal visit (See Appendix 3). Then the maximum regionally varied predicted probability range is observed among variables at age at first birth and age at first marriage. These variables have high random effects on obstetric fistula compare to the other predictor variables and these are also used in the random coefficient model.

Table 4.7: The Predicted probability of OF among women's by Regions with predictors

Covariates	Predicted log odds		Predicted probability of (Maximum-Minimum)
	Minimum	Maximum	
Place of Residence	-3.451691	1.96662	0.846529
Educational Status	-3.451691	2.601268	0.900225
Age at first Birth	-4.675922	3.052884	0.945676
Employment Status	-3.451691	2.601268	0.900225
Age at first Marriage	-3.451691	5.469893	0.965088
Place of Delivery	-6.695044	1.966620	0.876012
Follow up of antenatal care	-6.398359	2.705277	0.935676

The deviance-based chi-square value for the empty model shown in Table 4.8 is the difference in -2log likelihood between an empty model of single level logistic regression (3067.6296) and empty model of multilevel logistic regression (2941.6786) (See Appendix 2; output 2.1 and output 2.2), which is to be compared with the critical value from the chi-squared distribution with 1 degree of freedom. The significance of this test implies that an empty multilevel model is better than an empty single level model. Actually the AIC value of the empty model (AIC=2945.679) is larger than that of random intercept model (AIC=2365.704), meaning that the random intercept model is better than the empty multilevel model in predicting incidence of obstetric fistula across regions. Similarly, the significant deviance-based chi-square value indicates that the random intercept is a better fit than the empty multilevel logistic model. The deviance-based chi-square test of random effects for random coefficient model is not statistically significant (p=0.2666) and have larger AIC and BIC (See Appendix 2; output 2.4).

Therefore, based on deviance-based chi-square and AIC results (See Table 4.8) we conclude that random intercept multilevel model is better than other multilevel logistic regression model to predicting incidence of obstetric fistula among regions.

Table 4.8: Summary of Multilevel Logistic Regression Model selection criteria based on deviance based chi-square test statistics.

		Empty model	Random intercept model	Random coefficient model
Model selection Criteria	-2*log likelihood	2941.6786	2329.7038	2323.2744
	Deviance based Chi-square test	125.9510	611.9748	6.4294
	P-value	.0000*	.0000*	0.2666
Model fit Diagnosis	AIC	2945.679	2365.704	2369.274
	BIC	2957.807	2474.856	2508.746

***** Significance at 5%

4.4.2 Multilevel Empty with Random Intercept Logistic Regression Analysis

The deviance-based Chi-square (χ^2 =125.951, P-value<0.0001) shows empty with random effect is better than the empty model without random effect (See Table 4.8). According to the result Table 4.9 the variance of the random factor ($\text{Estimate} = 0.4481065, \text{S.E} = 0.2102528$) and the Wald test statistic is (the square of Z), where $Z^2 = (0.4481065/0.2102528)^2 = 4.5423$ which is compared with a chi-squared distribution on 1 degree of freedom becomes a p-value less than 0.05. Therefore, we conclude that there is significant variation in women's suffering from obstetric fistula. The intercept $\beta_0 = -1.564172$ is reflects as the average overall odds of incidence of obstetric fistula. This can be further interpreted as the average probability of obstetric fistula incidence everywhere in Ethiopia is $\exp(-1.564172)/\,[1 + \exp(\,-1.564172)] = 0.173$.

The intra-region correlation coefficient (rho) is a measure of variation of incidence of obstetric fistula with in region. The intra region correlation (intra correlation coefficient) in intercept only model is determined by using equation (3.32) and it becomes (ICC=0.1199), meaning that 11.99%

of variation in the incidence of obstetric fistula can be explained by grouping in regions (higher level units). The remaining 88.01% of the variation is explained within region (lower level units).

Table 4.9: Results of empty with random intercept multilevel logistic regression model analysis

Fixed Part	**Coefficient**	**S.E**	**Z-Value**	**P-Value**
$\beta_0 = \text{intercept}$	-1.564172	0.2100095	-7.45	0.000*
Random Part	**Estimate**	**S.E**	**Z-Value**	**P-Value**
Level two variance $\left(\sigma_0{}^2 = Var(u_{0j})\right)$	0.4481065	0.2102528	2.1313	0.0165*
Intra-region correlation (rho)	0.1199			
Deviance based Chi-square	125.951			0.000*
Deviance	1470.8393			
AIC	2945.679			

***** Significant at 5%

4.4.3 Multilevel Random Intercept Logistic Regression Analysis

In multilevel random intercept logistic regression model we allowed the probability of the incidence of obstetric fistula to vary across regions, but we assumed that the effects of explanatory variables are the same for each region. That is, the random intercept varies across regions, but levels of explanatory variables are fixed across region in predicting incidence of obstetric fistula in Ethiopia.

According to the result of the random intercept model, the fixed part showed that place of residence, educational status, age at first birth, employment status, age at first marriage, place of delivery and follow up of antenatal care were found to be significant determinants of variation in the incidence of obstetric fistula among regions (See Table 4.10). The estimated coefficient and odds ratio for random intercept model have a similar interpretation as multiple logistic regression (Hasinur and Ewart, 2011) as discussed above.

The random part of empty random intercept multilevel model show that the intercept variance of the random effect is 0.44810650, whereas the intercept variance for the random intercept model is 0.4309071. The variance of random effect of the intercept multilevel model decreased compared to random effects of intercept of empty random intercept model. The reduction of the random effect of the intercept variance is due to the inclusion of fixed explanatory variables. That is, taking in to account the fixed independent variables can provide extra predictive value on incidence of obstetric fistula in each region.

The result presented in Table 4.10 shows that women's who had primary and secondary education, delivered from home, delivered from a particular position (others), take antenatal care for more than one day during pregnancy and women's whose first birth and marriage at in the age range 15 years and above were less likely to have experiencing obstetric fistula compared to the corresponding reference category. Whereas, women who reside in rural part and had not currently working were more likely to have experiencing obstetric fistula compared to women's who reside in urban part and had currently working respectively.

Table 4.10: Results of random intercept multilevel logistic model analysis

Fixed Effect Covariates		Coefficient	P-Value
Place of Residence	Urban (Ref)		
	Rural	1.576699	0.000*
Educational Status	No Education (Ref)		
	Primary	-2.278613	0.000*
	Secondary and Higher	-1.647625	0.000*
Employment Status	Currently working (Ref)		
	No Currently working	0.2907657	0.010*
Age at first Birth	<15 years (Ref)		
	15-19 years	-0.745071	0.002*
	20-24 years	-1.722449	0.000*
	25 and above years	-2.025014	0.000*

Age at first Marriage	<15 years (Ref)			
	15-19 years		-2.019424	0.000*
	20-24 years		-1.672184	0.000*
	25 and above years		-0.4038004	0.279
Place of Delivery	Home (Ref)			
	Health Center		-1.610273	0.000*
	Others		-0.860004	0.126
Follow up of Antenatal Care	No antenatal visit (Ref)			
	1-3 days		-1.551949	0.000*
	4-6 days		-1.551782	0.000*
	7 days and Above		-2.000169	0.000*
	Do not Know		-0.8827674	0.322
Constant			2.248204	0.000*
Random Part	**Estimate**	**S.E**	**Z-Value**	**P-value**
Level-two variance $\left(\sigma_0{}^2 = Var(u_{0j})\right)$	0.4309071	0.2061447	2.09031	0.036*
Model Selection Criteria				
Deviance Based Chi-square			611.9748	0.000*
Deviance			1164.8519	
AIC			2365.704	

***** Significance at 5%

4.5 Discussions of Results

This study aims to identify some determinants of obstetric fistula based on Ethiopian Demographic and Health Survey (EDHS 2005) data. Accordingly descriptive analysis, binary logistic regression and multilevel logistic regression techniques were used. In general, the results from this study were a little consistent with most previous studies in terms of the risk factors of obstetric fistula. The results which are obtained are discussed as follow:

The descriptive analysis of this study shows that the prevalence of obstetric fistula in Ethiopia was 18.8%. Based on the result of this study, woman who live in Amhara, Oromia, Gambella, SNNP, Somali, Affar and Diredawa regions were more likely to have experiencing obstetric fistula than women who live in Addis Ababa region.

This study found that experiencing of obstetric fistula was significantly associated with age at first birth. Women whose first birth at in the age range between 15-19 years were 51.9% less likely to suffer obstetric fistula than women whose first birth at in the age range <15 years. On the same way, women whose first birth at in the age range 25 years and above were 86.9% less likely to suffer obstetric fistula than women whose first birth at in the age range <15 years. This result is in agreement with (Muleta, 2004) and (Roka *et al*., 2013), revealed that early age at pregnancy has one of the factors leading to increase risks of obstetric fistula with particular reference to adolescent's women (12-19 years). This finding shows that there is an inverse relationship between age at first birth and prevalence of fistula.

The finding also shows that place of delivery and follow up of antenatal care were significantly associated with the incidence of obstetric fistula. Women's who delivered from health facility and follow antenatal care for more than one day were less likely to exposed obstetric fistula than those women's who delivered from their homes and had no antenatal care visits. This result is in agreement with (Roka *et al*., 2013) suggested that major risk factors for obstetric fistula were not attending antenatal care and living far away from health facility. Similarly, the finding is consistent with (Muleta, 2004) found that women had little or no access to healthcare, prenatal or emergency obstetric care were the most frequently cited problems suffered to obstetric fistula. Moreover, the result is also correspondence with (Mohamed *et al*., 2008) revealed that the victim of obstetric fistula was mostly not attend on regular antenatal care and most deliveries were carried at home, attended by traditional birth attendants.

The result of this study indicates that incidence of obstetric fistula was significantly associated with educational status. Women's who had primary education, secondary and higher education were less likely to suffer obstetric fistula than illiterate women's. This result is consistent to (Roka *et al*., 2013; Wall, 2006 and Yeakey, 2009) found that the major risk factors for obstetric fistula were illiteracy. Similarly, the finding is correspondence with (Tebekew, 2011), show that women with secondary and higher education were 78 % less likely to affect obstetric fistula than those who had no education. Furthermore, the result is also in agreement with Mohamed *et al.*, 2008 revealed that the victim of obstetric fistula was mostly illiterate. Another study done by (Tebeu, 2009) gives a general conclusion to this important factor; education plays an important role in the occurrence of obstetric fistula, and in maternal mortality and morbidity.

In this study, place of residence is a major causing problem of obstetric fistula, especially in developing country like Ethiopia. The study showed that the likelihood of women's who reside in rural area was 5.167 times more likely to affect obstetric fistula than that of women who reside in urban area. Many literatures reviewed about this important determinant factor of obstetric fistula. For instance a study done by (Wall, 2006; Holme *et al* and Johnson 2007; Nathan, 2008) showed that the major risk factors for obstetric fistula were rural place of residence. This finding is also corresponds to a study employed in Ethiopia revealed that majority of rural women were affected by obstetric fistula (Tebekew, 2011).

The model of this study revealed that likelihood of having obstetric fistula among women's had no currently employed was 1.328 times more likely to have experience of obstetric fistula than women's who had currently employed. This finding is consistent with a study done in West Pokot by (Mabeya, 2003) revealed that the majority of fistula incidents occurred in women had no specific occupation.

CHAPTER FIVE

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The study identified that demographic, socio-economic, environmental and health related variables have an important effect on determinants of obstetric fistula in Ethiopia.

According to this study, multiple logistic regression showed that region, place of residence, educational status, age at first marriage, age at first birth, employment status, place of delivery and follow up of antenatal care were all important factors to determining the incidence of obstetric fistula in Ethiopia. Where, body mass index, marital status and wealth index were found to be insignificant factors of determining obstetric fistula in Ethiopia.

From the results of multilevel logistic regression analysis among all the three models, the random intercept multilevel model provided the best fit for the data under consideration. It showed that the prevalence of obstetric fistula was varied among regions. Additionally, in empty with random intercept model and random intercept and fixed coefficient models the overall variance of the constant term was found to be significant, which reflects the existence of differences in incidence of obstetric fistula across region. The significant determinant factors for the variations of prevalence of obstetric fistula among regions were place of residence, educational status, age at first marriage, age at first birth, employment status, place of delivery and follow up of antenatal care.

5.2 Recommendations

Based on the findings of this study, the following recommendations are forwarded:

- ✓ To avoid the risk of obstetric fistula due to pregnancy and delivery, strengthening family planning and antenatal care services should be addressed extensively.
- ✓ Awareness has to be given for the society on the risk of early marriage and early pregnancy. So that, the Ethiopian government should ensure the practice of the law against early marriage through enhancing family and community awareness about the dangers of early marriage and early pregnancy.

- ✓ On the basis of the study findings, improving the educational and employment status of women with the aim of enhancing their socio-economic status is vital for their health wellbeing.
- ✓ Advocate for healthcare systems which provide accessible, quality maternal health care, including family planning, skilled care at birth, basic and comprehensive emergency obstetric care, and affordable treatment of obstetric fistula.
- ✓ Health care providers, women and their families need comprehensive information on causes of obstetric fistula, so that they can be better prepared to help in times of injury during birth. This includes information on childbirth, the 'danger signs' that indicate obstetric complications, the imperative to take quick action when signs and symptoms of obstetric complications occur.
- ✓ Contribute to the development and dissemination of policies, protocols of practice which prevent obstetric fistula.
- ✓ The Ethiopian government should contribute to education of communities and families regarding prevention of obstetric fistula.

5.3 Limitations of the Study

The study has different limitations the major limitations of the study are:-

- ✓ The study is conducted based on secondary data which might have incomplete and biased information.
- ✓ As different literature pointed out there are different important factors that are assumed to have impacts on determinants of obstetric fistula in Ethiopia such as age at developing fistula and mode of delivery. However, we did not get data on these variables to include in the analysis. Similarly, there are also some predictor variables not included in the analysis due to missing values and non-responses. This may make the study somewhat incomplete.
- ✓ The data used in this study are from the EDHS 2005. Thus, the results may not necessarily reflect the current situation of Ethiopia.

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Appendixes

Appendix 1: Results of Binary and Multiple Logistic Regression Analysis Using SPSS 16.0

Table 1.1: Dependent Variable Encoding

Original Value	Internal Value
No	0
Yes	1

Table 1.2: Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Step	515.105	33	0
Block	515.105	33	0
Model	515.105	33	0

Table 1.3: Contingency Table for Hosmer and Lemeshow Test

Being Not Experienced Obstetric Fistula		Being Experienced Obstetric Fistula		Total
Observed	Expected	Observed	Expected	
313	309.114	5	8.886	318
301	302.781	19	17.219	320
298	293.39	20	24.61	318
285	285.509	34	33.491	319
263	266.824	43	39.176	306
268	271.252	50	46.748	318
260	262.059	58	55.941	318
249	244.172	68	72.828	317
212	213.877	106	104.123	318
133	133.02	193	192.98	326

Table 1.4: Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
Constant	-1.466	0.045	1.04E+03	1	0	0.231

Table 1.5: Results of diagnostic tests for outliers and influential value

Types of Diagnostic	**Cases**	**Minimum**	**Maximum**
Analog of Cook's influence statistics	3178	0.00003	0.47993
Leverage value	3178	0.00241	0.21054
DFBETA for constant	3178	-0.29077	0.48179
DFBETA for Place of Residence(1)	3178	-0.02518	0.03564
DFBETA for Educational Status(1)	3178	-0.02627	0.02460
DFBETA for Educational Status(2)	3178	-0.02494	0.02234
DFBETA for Age at 1st Birth(1)	3178	-0.06329	0.04396
DFBETA for Age at 1st Birth(2)	3178	-0.06042	0.04619
DFBETA for Age at 1st Birth(3)	3178	-0.05196	0.03713
DFBETA for 1st Marriage(1)	3178	-0.11424	0.08612
DFBETA for 1st Marriage(2)	3178	-0.11316	0.08790
DFBETA for 1st Marriage(3)	3178	-0.10031	0.08807
DFBETA for Employment Status(1)	3178	-0.00847	0.00620
DFBETA for Region 1	3178	-0.08524	0.03403
DFBETA for Region 2	3178	-0.08541	0.07966
DFBETA for Region 3	3178	-0.08243	0.03480
DFBETA for Region 4	3178	-0.08462	0.03373

DFBETA for Region 5	3178	-0.08474	0.17018
DFBETA for Region 6	3178	-0.08306	0.03946
DFBETA for Region 7	3178	-0.08302	0.03410
DFBETA for Region 8	3178	-0.07745	0.09258
DFBETA for Region 9	3178	-0.07503	0.03704
DFBETA for Region 10	3178	-0.07815	0.04271
DFBETA for Follow up of antenatal(1)	3178	-0.39903	0.29492
DFBETA for Follow up of antenatal(2)	3178	-0.39761	0.29622
DFBETA for Follow up of antenatal(3)	3178	-0.39851	0.29811
DFBETA for Follow up of antenatal(4)	3178	-0.38463	0.30453
DFBETA for Place of Delivery(1)	3178	-0.51038	0.03176
DFBETA for Place of Delivery(2)	3178	-0.53173	0.03122

Appendix 2: Multilevel Logistic Regression Results Using STATA 11

Output 2.1: Result of empty single level logistic regression model for predicting the incidence of OF

```
. logit ExOF

Iteration 0:   log likelihood = -1533.8148
Iteration 1:   log likelihood = -1533.8148

Logistic regression                               Number of obs   =       3178
                                                  LR chi2(0)      =      -0.00
                                                  Prob > chi2     =          .
Log likelihood = -1533.8148                       Pseudo R2       =    -0.0000

------------------------------------------------------------------------------
        ExOF |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |  -1.466079   .0454439   -32.26   0.000    -1.555147    -1.37701
```

Output 2.2: Result of empty multilevel logistic regression model for predicting the incidence of obstetric fistula.

```
. xtmelogit ExOF || Reg:,cov(unstr)var
Note: single-variable random-effects specification; covariance structure set to identity

Refining starting values:

Iteration 0:   log likelihood = -1472.1249
Iteration 1:   log likelihood = -1470.9121
Iteration 2:   log likelihood = -1470.8433

Performing gradient-based optimization:

Iteration 0:   log likelihood = -1470.8433
Iteration 1:   log likelihood = -1470.8393
Iteration 2:   log likelihood = -1470.8393

Mixed-effects logistic regression               Number of obs      =      3178
Group variable: Reg                             Number of groups   =        11

                                                Obs per group: min =       104
                                                               avg =     288.9
                                                               max =       561

Integration points =   7                        Wald chi2(0)       =         .
Log likelihood = -1470.8393                     Prob > chi2        =         .

------------------------------------------------------------------------------
        ExOF |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |  -1.564172   .2100095    -7.45   0.000    -1.975783   -1.152561
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
Reg: Identity                |
                  var(_cons) |   .4481065   .2102528      .1786467    1.124003
------------------------------------------------------------------------------
LR test vs. logistic regression: chibar2(01) =   125.95 Prob>=chibar2 = 0.0000

. estimates stats

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |   3178           .   -1470.839      2     2945.679    2957.807
-----------------------------------------------------------------------------
```

Output 2.3: Results of random intercept multilevel logistic model for predicting the incidence of obstetric fistula.

```
. xtmelogit ExOF i. PlR i. EduSta i. Ag1Bi i. EmSt i. Ag1Ma i. PlDel i. FolAnt|| Reg:,cov(unstr)v
> ar
Note: single-variable random-effects specification; covariance structure set to identity

Refining starting values:

Iteration 0:   log likelihood = -1172.7001  (not concave)
Iteration 1:   log likelihood = -1169.1315
Iteration 2:   log likelihood = -1164.9496

Performing gradient-based optimization:

Iteration 0:   log likelihood = -1164.9496
Iteration 1:   log likelihood = -1164.8525
Iteration 2:   log likelihood = -1164.8519
Iteration 3:   log likelihood = -1164.8519

Mixed-effects logistic regression               Number of obs      =      3178
Group variable: Reg                             Number of groups   =        11

                                                Obs per group: min =       104
                                                               avg =     288.9
                                                               max =       561

Integration points =   7                        Wald chi2(16)      =    381.45
Log likelihood = -1164.8519                     Prob > chi2        =    0.0000
```

ExOF	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.PlR	1.576699	.1857746	8.49	0.000	1.212588	1.940811
EduSta						
1	-2.278613	.2335176	-9.76	0.000	-2.736299	-1.820927
2	-1.647625	.2446611	-6.73	0.000	-2.127152	-1.168098
Ag1Bi						
1	-.745071	.2423118	-3.07	0.002	-1.219993	-.2701486
2	-1.722449	.1939113	-8.88	0.000	-2.102508	-1.34239
3	-2.025014	.3323507	-6.09	0.000	-2.676409	-1.373619
1.EmSt	.2907657	.1132581	2.57	0.010	.0687839	.5127474
Ag1Ma						
1	-2.019424	.3862026	-5.23	0.000	-2.776367	-1.262481
2	-1.672184	.3727067	-4.49	0.000	-2.402675	-.9416919
3	-.4038004	.3733357	-1.08	0.279	-1.135525	.3279241
PlDel						
1	-1.610273	.3227083	-4.99	0.000	-2.24277	-.9777766
2	-.860004	.5625789	-1.53	0.126	-1.962638	.2426303
FolAnt						
1	-1.551949	.2318449	-6.69	0.000	-2.006357	-1.097542
2	-1.551782	.2432034	-6.38	0.000	-2.028452	-1.075112
3	-2.000169	.4444309	-4.50	0.000	-2.871237	-1.1291
4	-.8827674	.8908386	-0.99	0.322	-2.628779	.8632442
_cons	2.248204	.4780733	4.70	0.000	1.311197	3.18521

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
Reg: Identity				
var(_cons)	.4309071	.2061447	.1687219	1.100515

```
LR test vs. logistic regression: chibar2(01) =   101.94 Prob>=chibar2 = 0.0000
```

```
. xtmelogit ,or

Mixed-effects logistic regression               Number of obs      =      3178
Group variable: Reg                             Number of groups   =        11

                                                Obs per group: min =       104
                                                               avg =     288.9
                                                               max =       561

Integration points =   7                        Wald chi2(16)      =    381.45
Log likelihood = -1164.8519                     Prob > chi2        =    0.0000
```

ExOF	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.PlR	4.838958	.8989556	8.49	0.000	3.362174	6.964396
EduSta						
1	.1024261	.0239183	-9.76	0.000	.0648097	.1618756
2	.1925066	.0470989	-6.73	0.000	.1191763	.3109579
Ag1Bi						
1	.4747006	.1150256	-3.07	0.002	.2952321	.7632661
2	.1786282	.034638	-8.88	0.000	.1221497	.2612207
3	.131992	.0438676	-6.09	0.000	.0688098	.2531891
1.EmSt	1.337451	.1514771	2.57	0.010	1.071205	1.669873
Ag1Ma						
1	.1327319	.0512614	-5.23	0.000	.0622643	.2829513
2	.1878365	.0700079	-4.49	0.000	.0904756	.3899675
3	.6677774	.2493051	-1.08	0.279	.3212535	1.388084
PlDel						
1	.199833	.0644878	-4.99	0.000	.106164	.3761465
2	.4231604	.2380611	-1.53	0.126	.1404873	1.274597
FolAnt						
1	.2118346	.0491128	-6.69	0.000	.1344777	.3336904
2	.2118701	.0515275	-6.38	0.000	.131539	.3412595
3	.1353124	.060137	-4.50	0.000	.0566288	.323324
4	.4136366	.3684835	-0.99	0.322	.0721665	2.37084

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
Reg: Identity				
sd(_cons)	.6564351	.1570183	.4107577	1.049054

```
LR test vs. logistic regression: chibar2(01) =   101.94 Prob>=chibar2 = 0.0000

. estimates stats
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	3178	.	-1164.852	18	2365.704	2474.856

Output 2.4: Results of random coefficient multilevel logistic regression model for predicting the incidence of obstetric fistula.

```
. xtmelogit ExOF i. PlR i. EduSta i. Ag1Bi i. EmSt i. Ag1Ma i. PlDel i. FolAnt || Reg: Ag
> 1Ma Ag1Bi, cov(unstr)var

Refining starting values:

Iteration 0:   log likelihood = -1188.7777  (not concave)
Iteration 1:   log likelihood = -1181.2637  (not concave)
Iteration 2:   log likelihood = -1172.9473

Performing gradient-based optimization:

Iteration 0:   log likelihood = -1172.9473  (not concave)
Iteration 1:   log likelihood = -1165.9827  (not concave)
Iteration 2:   log likelihood = -1164.8068  (not concave)
Iteration 3:   log likelihood =  -1163.974
Iteration 4:   log likelihood = -1162.6424  (not concave)
Iteration 5:   log likelihood =  -1162.181
Iteration 6:   log likelihood = -1161.6647  (not concave)
Iteration 7:   log likelihood = -1161.6503
Iteration 8:   log likelihood = -1161.6437
Iteration 9:   log likelihood = -1161.6377
Iteration 10:  log likelihood = -1161.6372
Iteration 11:  log likelihood = -1161.6372

Mixed-effects logistic regression               Number of obs      =      3178
Group variable: Reg                             Number of groups   =        11

                                                Obs per group: min =       104
                                                               avg =     288.9
                                                               max =       561

Integration points =   7                        Wald chi2(16)      =    361.23
Log likelihood = -1161.6372                     Prob > chi2        =    0.0000
```

ExOF	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.PlR	1.599925	.1871084	8.55	0.000	1.233199	1.96665
EduSta						
1	-2.252381	.2347646	-9.59	0.000	-2.712511	-1.792251
2	-1.639519	.2460178	-6.66	0.000	-2.121705	-1.157333
Ag1Bi						
1	-.6123365	.2562644	-2.39	0.017	-1.114605	-.1100675
2	-1.602125	.2352606	-6.81	0.000	-2.063228	-1.141023
3	-1.960604	.3867579	-5.07	0.000	-2.718635	-1.202572
1.EmSt	.2860051	.1137762	2.51	0.012	.0630078	.5090024
Ag1Ma						
1	-1.989761	.4103833	-4.85	0.000	-2.794097	-1.185424
2	-1.614475	.3870319	-4.17	0.000	-2.373044	-.8559064
3	-.3571639	.3937816	-0.91	0.364	-1.128962	.4146339
PlDel						
1	-1.610585	.3267507	-4.93	0.000	-2.251005	-.9701654
2	-.902186	.5702542	-1.58	0.114	-2.019864	.2154917
FolAnt						
1	-1.569767	.2324552	-6.75	0.000	-2.02537	-1.114163
2	-1.540846	.2424632	-6.35	0.000	-2.016065	-1.065627
3	-1.956434	.4551408	-4.30	0.000	-2.848494	-1.064374
4	-.8524555	.9000137	-0.95	0.344	-2.61645	.9115389
_cons	2.110284	.5090045	4.15	0.000	1.112653	3.107914

```
------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
Reg: Unstructured            |
                  var(Ag1Ma) |    .004473    .025909      5.25e-08    381.1116
                  var(Ag1Bi) |   .0384787   .0375255      .0056899    .2602167
                  var(_cons) |   .5882344   .3650258      .1743178    1.984994
            cov(Ag1Ma,Ag1Bi) |  -.0008539   .0236416     -.0471905    .0454827
            cov(Ag1Ma,_cons) |  -.0102483   .0785909     -.1642837    .1437871
            cov(Ag1Bi,_cons) |  -.1284465    .094011     -.3127045    .0558116
------------------------------------------------------------------------------
LR test vs. logistic regression:     chi2(6) =   108.37   Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

. estimates stats

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |   3178           .   -1161.637     23     2369.274    2508.746
-----------------------------------------------------------------------------
```

Appendix 3: List of Figures

Fig 3. 1: Simple Bar chart of prevalence of obstetric fistula

Fig 3. 2: Predicted Probability of Obstetric fistula by Place of Residence vs Region

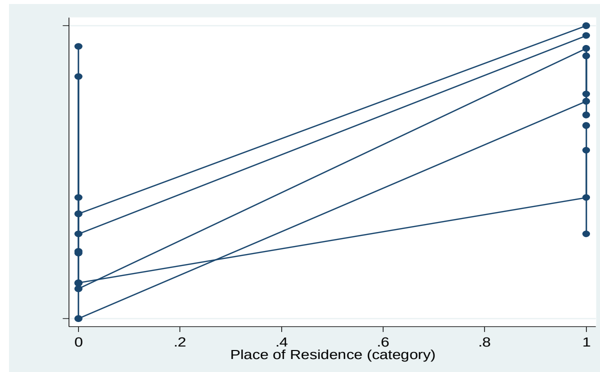

Fig 3. 3: Predicted Probability of Obstetric fistula by Educational Status vs Region

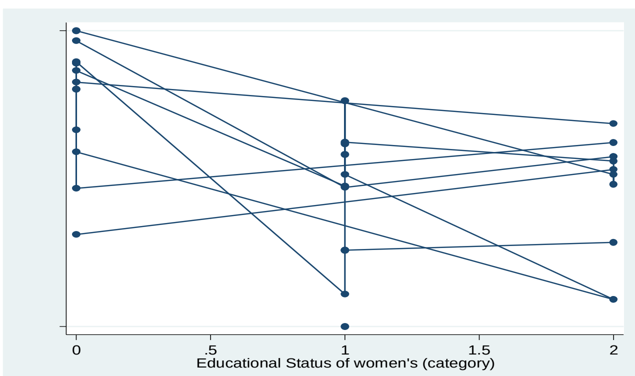

Fig 3. 4: Predicted Probability of Obstetric fistula by Age at first Birth vs Region

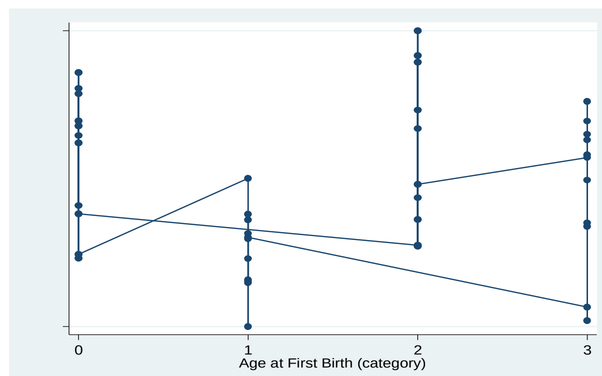

Fig 3. 5: Predicted Probability of Obstetric fistula by Employment Status vs Region

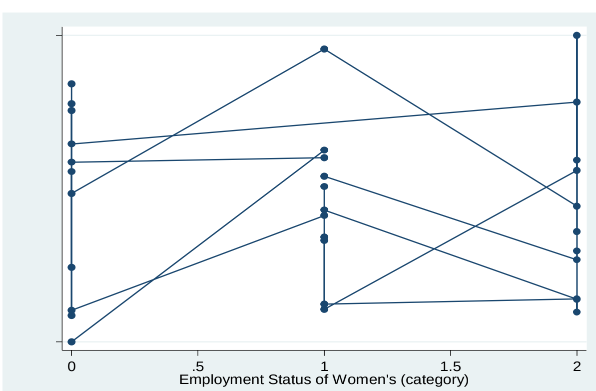

Fig 3. 6: Predicted Probability of Obstetric fistula by Age at first Marriage vs Region

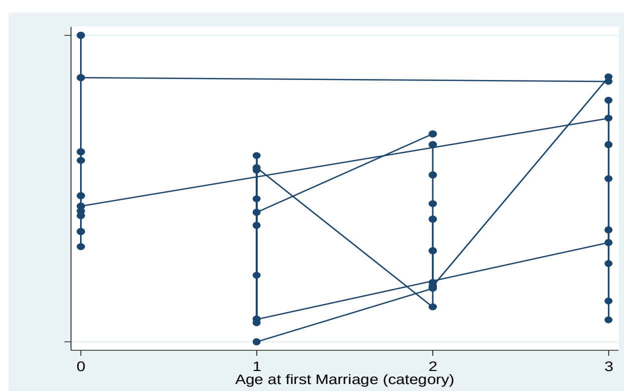

Fig 3. 7: Predicted Probability of Obstetric fistula by Follow up of Antenatal Care vs Region

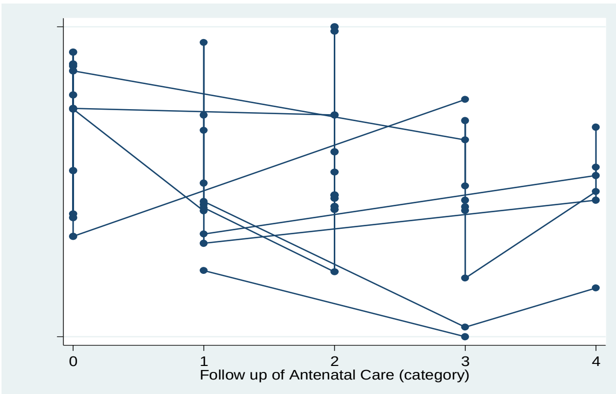

Fig 3. 8: Predicted Probability of Obstetric fistula by Place of Delivery vs Region